FROM FIELD TO HOME: ASSESSING AIR INFILTRATION AND SOIL TRACK-IN TRANSPORT PATHWAYS OF AGRICULTURAL PESTICIDES INTO FARMWORKERS' HOME AND IDENTIFYING RISK FACTORS FOR INCREASED IN-HOME PESTICIDE LEVELS

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Anastasia Julia Sugeng, titled *From Field to Home: Assessing Air Infiltration And Soil Track-In Transport Pathways Of Agricultural Pesticides Into Farmworkers' Home And Identifying Risk Factors For Increased In-Home Pesticide Levels* and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

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~~~In the name of God, the Most Gracious, the Most Merciful~~~

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who have relentlessly supported me and this entire process of pursuing my Ph.D.,

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ABSTRACT

Farmworkers and their families may experience increased levels of agricultural pesticides in their homes due to both (1) take-home/soil track-in on shoes, clothes and skin, and (2) air infiltration from nearby agriculture fields via agricultural pesticide drift in the vapor phase or adhered to resuspended soil particles. This dissertation estimates the relative contributions o the take-home/soil track-in and air infiltration pathways of agricultural pesticides into homes, as well as identifies the risk factors for increased in-home agricultural pesticide levels for farmworkers and their families living near agriculture fields. Samples of outdoor air, yard soil, and house dust from 21 farmworkers' homes in Yuma County, Arizona were collected and analyzed for a suite of agricultural pesticides. To capture household information, such as behaviors, demographics, and housing structure, a participant questionnaire was administered at the time of the sampling. A pesticide transport model was developed, evaluated, and applied to quantify relative contributions of the air infiltration and the take-home/soil track-in pathways of agricultural pesticides into the house dust of the farmworkers' homes. To explore a wide-range of potential risk factors for increased agricultural pesticide levels in the homes, traditional statistical methods and Classification and Regression Tree (CART) analyses were used. The results of this study, found that the air infiltration pathway contributes to over 90% of some agricultural pesticides in the house dust found in the farmworkers' homes. In addition, among the influential risk factors for increased in-home agricultural pesticide levels was the home being a closer distance to an agricultural field, as well as the home having carpeted floors, more farmworkers per square footage of the

home, and less months of heating and cooling the home. It is suggested that future intervention efforts to reduce in-home agricultural pesticide levels put more emphasis on targeting the air infiltration pathway, and take into consideration relevant risk factors for increased pesticide levels in the home.

CHAPTER 1

INTRODUCTION

1.1 Dissertation Motivation

The transport of pesticides away from agricultural fields and into the homes of farmworkers is a major environmental health and public health concern (Rawlings et al., 1998; Anderson et al., 2000; Faustman et al., 2000; Eskenazi et al., 2007). The two main pathways in which pesticides applied to agricultural fields can be transported to nearby homes are through air and soil transport (Figure 1-1). Transport through the air can first occur via the resuspension of pesticide-contaminated soil particles. Transport through the air can additionally occur via pesticide drift in the vapor phase after a spraying event or volatilization out of treated soil. Pesticides in the air may infiltrate into the home and then either settle into the house dust or exfiltrate out of the home. This may be referred to as the air infiltration pathway. Alternatively, pesticides applied in agricultural fields may settle into the soil which farmworkers can inadvertently take home with them on their shoes, clothes, and skin, and ultimately enter the home through soil track-in. Pesticides may then either settle into the house dust or exit the house through removal processes. This can be referred to as the take-home/soil track-in pathway.

Authors of previous pesticides studies in agricultural communities have posited the significance of soil transport (McCauley et al., 2003; Curwin et al., 2005; Lozier et al., 2012), air transport (Richards et al., 2001; Fenske et al., 2002; Gunier et al., 2011), and a combination of the two pathways (Simcox et al., 1995; Ward et al., 2006; Harnly et al., 2009). However, the relative importance of the air infiltration pathway of agricultural pesticides verses the take-home/soil track-in pathway into the home, and the factors that influence the agricultural pesticide transport from fields to homes via both pathways, remain under-characterized. For example, in a previous large-scale community-wide intervention study, Para Niños Saludables, the researchers aimed to reduce agricultural pesticide levels in the house dust of farmworkers' homes by modifying farmworkers' behaviors related to the take-home/soil track-in pathway (Thompson et al., 2008; Strong et al., 2009) over a period of four years. After the intervention, there was no significant reduction in agricultural pesticide levels found in farmworkers' house dust or urine, despite notable alterations to behaviors relevant to the soil track-in, such as the farmworkers removing shoes promptly upon arriving home from work (ibid). One possible reason for the limited effectiveness of this intervention could be that it only focused on the take-home/soil track-in pathway, but it did not incorporate factors related to air infiltration, which may be the more prominent pathway of agricultural pesticides into the home.

Further evidence that air infiltration may be the more prominent transport pathway of agricultural pesticides into house dust is based on a study which used a soil contaminant transport model to estimate the relative contributions of the soil track-in and air infiltration pathways of inorganic contaminants into the house dust of Southern Arizona homes, along with the residence time of particles in the house dust (Beamer et al., 2009a). In that application, it was estimated that the air infiltration pathway contributed to more than 85% of the arsenic and lead measured in the house dust despite the fact that ambient air levels were low for both arsenic and lead (<1 ng/m^3) compared to the levels in the soil (5-10 mg/kg) (ibid). This showed that air infiltration was the main transport pathway of inorganic contaminants into the house dust. Results of that application also showed that the residence time of floor particles was only 61 days (Beamer et al., 2009a), which suggests that detection of inorganic contaminants over a long period of time may be the result of continued transport into the home. However, whether there would be similar relative contributions of each pathway into the home and the residence times for agricultural pesticides has not been previously assessed.

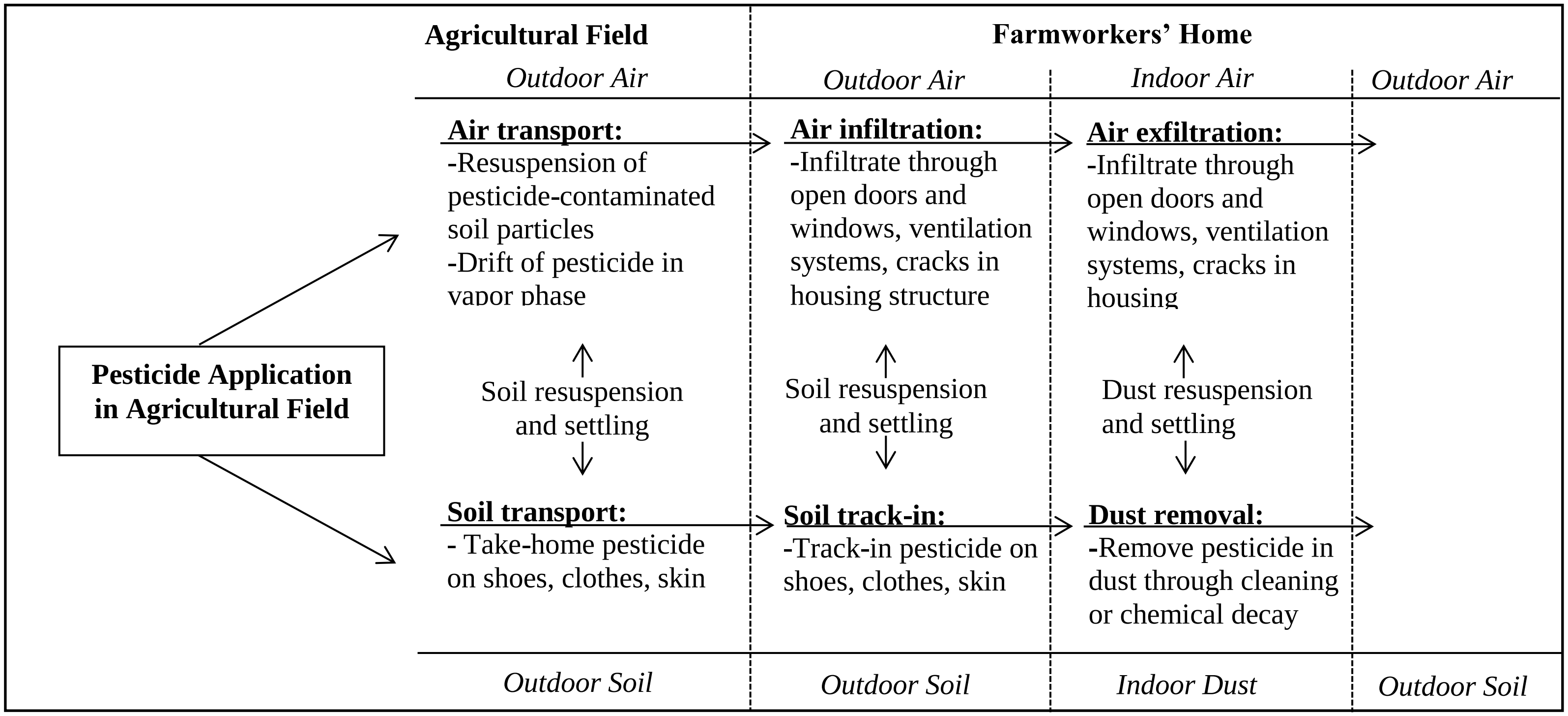


Figure 1-1: Depiction of Pesticide Transport from Agricultural Fields to Farmworkers' Homes via Air and Soil Pathways

1.2 Dissertation Overview

This dissertation is composed of four major aims and seven additional Chapters. Multiple approaches were used to: assess the transport pathways of pesticides from agricultural fields into farmworkers' homes, identify risk factors for increased agriculture pesticide levels in the homes, and demonstrate the significance of these findings and their contribution to the fields of environmental health and public health.

1.2.1 Field Sampling and Pesticide Transport Modeling

The first major aim of this dissertation was to use a combination of field sampling and modeling to quantitatively estimate the relative contributions of the air infiltration transport pathway of agricultural pesticides into farmworkers' homes verses the take-home/soil track-in pathway, as well as estimate the residence time (i.e., time of persistence) of agricultural pesticides in the house dust. The major hypotheses of the first major aim were that: (1) air infiltration is the dominant pathway of agricultural pesticides into the homes compared to the take-home/soil track-in pathway and, (2) the residence time of the agricultural pesticides in the house dust is less than one year.

Chapter 2 of this dissertation describes the field sampling component of this project in which samples of outdoor air, yard soil, and house dust from 21 farmworkers' homes in Yuma County, Arizona were collected and analyzed for the following agricultural pesticides: bifenthrin, carbaryl, DDT, endosulfan, permethrin, pronamide, and trifluralin. The pesticides analyzed were chosen according to the results of a pesticide hazard-ranking system developed by Ms. Sugeng, which was applied specifically to Yuma County (Sugeng, 2012; Sugeng et al., 2013). The hazard ranking system took into account the pounds of agricultural applications for each pesticide in Yuma County, Arizona, each pesticide's toxicity for multiple chronic health effects, and exposure potential based on each pesticide's intrinsic chemical characteristics. As such, the pesticides chosen for analysis were those considered to be up-to-date and relevant for the community being sampled. The effectiveness of using a hazard-ranking scheme to target agricultural pesticides in farmworkers' homes was also assessed and discussed.

Chapter 3 of this dissertation details the author's development, evaluation, and application of a pesticide transport model which was based on a previously developed soil contaminant transport model, co-developed by one of Ms. Sugeng's committee members, Dr. Beamer. Since the soil contaminant transport model was developed to understand the transport of inorganic contaminants into homes (Beamer et al., 2009a; Layton and Beamer, 2009), the current study modified that model to take into account pesticide decay in the environment and particle-vapor partitioning in the air, two processes that are not relevant to inorganic contaminants. The pesticide transport model was then evaluated and applied to estimate the relative contributions of the air infiltration and soil track-in pathways to the pesticide levels in sampled house dust from the farmworkers' homes, and to compute the residence time of the pesticides in the house dust. Chapter 2 and Chapter 3 together fulfill the first major aim of this dissertation and its associated hypotheses.

1.2.2 Identifying External Risk Factors for Increased Pesticide Levels

The second major aim of this dissertation was to identify relevant external risk factors for increased agricultural pesticide levels in the farmworkers' homes. The external risk factors were defined to be those factors not directly related to the farmworkers or their household. The first external risk factor category considered was the inherent chemical characteristics of the agricultural pesticides of interest, which varied drastically (Wauchope et al., 1992; MacKay et al., 2006; USEPA, 2014), and may provide insight into the transport of pesticides in the environment (Wauchope et al., 1992). The second external risk factor category considered was the microclimate/local weather conditions during the time of sampling, a factor that has long been thought to influence the drift and deposition of chemicals, such as pesticides, in the environment (Akesson and Yates, 1964; Bache and Johnstone, 1992). The third external risk factor category considered was the spatial and temporal distribution of pesticide applications in agricultural fields near the participants' homes. In recent years, the use of geographic information systems (GIS) has become an increasingly popular tool to better understand the spatial and temporal distribution of agricultural pesticide applications and the association with exposure risk and adverse health effects (Gunier et al., 2001; Ares et al., 2006, Posen et al., 2006; Luo et al., 2010). The main hypotheses for the second major aim of this dissertation were that: (1) chemical characteristics will be associated with detection frequency in outdoor air, yard soil, and household dust, and (2) microclimate/weather conditions during the time of sampling, along with spatial and temporal distributions of agricultural pesticide applications near the participants' homes prior to sampling, will be most strongly associated with detection of pesticides in the outdoor air. Chapter 4 of this dissertation addresses the second major aim and its hypotheses.

1.2.3 Identifying Household-Level Risk Factors for Increased Pesticide Levels

The third major aim of this dissertation was to identify relevant household-level risk factors for increased agricultural pesticide levels at the farmworkers' homes. The household-level risk factors were defined to be those factors directly relevant to the farmworkers or their household. Certain studies have identified the influence of household-level risk factors on agricultural pesticide levels in the house dust, including house proximity to the nearest agricultural field or orchard (Simcox et al., 1995; McCauley et al., 2001; Quandt et al., 2004), having a house that is difficult to clean (Quandt et al., 2004), and having a greater number of people living in the house (both in general and specifically employed in the agricultural industry) (McCauley et al., 2001). For the purposes of this dissertation, each potentially influential household-level risk factor was placed into one of the following categories: (1) household member characteristics (i.e., demographics, types of household residents, and household pets), (2) household behaviors (i.e., farmworker hygiene/take-home behaviors, cleaning and maintenance of the home, and temperature control and ventilation behaviors), and (3) housing structure characteristics (i.e., home size and age, ground and floor type, and temperature control and ventilation). The hypothesis for the third major aim of this dissertation was that most of the household-level risk factors associated with in-home agricultural pesticide levels would be housing structure characteristics related to the air infiltration pathway, and that these influential factors could not easily be modifiable by the family.

Chapter 5 of this dissertation explores relevant household-level risk factors that were captured through administration of a participant questionnaire completed during the sampling component of this dissertation project. The analyses in Chapter 5 were not hypothesis driven, but rather provided an exploratory approach to assessing the influence of the various household-level risk factors on increased in-home agricultural pesticide levels through a series of univariate analyses. Chapter 6 of this dissertation provides a multivariate approach to assessing the influence of household-level characteristics on the agricultural pesticide detection frequency in yard soil, outdoor air, and house dust in the farmworkers' homes by building a series of Classification and Regression Tree (CART) models. The CART models were used to (1) identify the most influential household-level risk factors associated with the soil track-in and air infiltration pathways of agricultural pesticides into the house dust, (2) differentiate between household-level risk factors related to household behaviors between housing structure characteristics, and (3) determine whether the influential household-level risk factors may easily be modifiable by the family. Chapter 5 and Chapter 6, in combination, fulfill the third major aim of this dissertation and its associated hypothesis.

1.2.4 Assessing Health Risks of Residential Exposure to Agricultural Pesticides

The fourth major aim of this dissertation was to estimate the level of risk to the farmworker families for developing cancer and non-cancer chronic health effects from residential exposure to agricultural pesticides. This was done by conducting aggregate and cumulative human health risk assessments based on the detected agricultural pesticides measured in the farmworkers' homes. The human health risk assessments determine whether the population is exposed at an "acceptable level," as determined by federal regulators, as well as provides insight into the extent to which the participants of this study are at an increased risk of potential adverse health effects, although this exposure risk notably only represents a portion of the overall potential pesticide exposure. The major hypothesis for the fourth major aim of this dissertation was that the aggregate and cumulative risk assessments would show that the risk of cancer and non-cancer chronic health effects were acceptable, according to federal guidelines, for non-dietary ingestion of the detected pesticides in yard soil and house dust and inhalation of the detected pesticides in the outdoor air.

Chapter 7 of this dissertation presents the process used to conduct the aggregate and cumulative human health risk assessments of the detected agricultural pesticides in the farmworkers' homes. The risk assessment process was limited to the agricultural pesticides of bifenthrin and permethrin, and took into account exposure through non-dietary ingestion of yard soil and house dust, along with inhalation of outdoor air. The human health risk assessment process consisted of the following four steps: (1) hazard identification, (2) dose-response assessment, (3) exposure assessment, and (4) risk characterization. The hazard identification step for bifenthrin and permethrin established that both pesticides are associated with cancer and non-cancer chronic health effects, such as endocrine disruption and reproductive/developmental toxicity. The toxicological dose-response data for cancer and non-cancer chronic health effects for these pesticides were obtained from the United States Environmental Protection Agency (USEPA) official documents. The exposure assessment was based on a set of assumptions from the 2011 Exposure Factors Handbook (USEPA, 2011) to calculate the exposure dose for cancer and non-cancer chronic health effects across the inhalation and ingestion exposure routes. Finally, the risk characterization step consisted of calculating the risk levels for cancer and non-cancer chronic health effects and compared those levels to standard levels of acceptable risk. Chapter 7 additionally offers a comparison to previous risk assessments, as well as a comparison between the measured bifenthrin and permethrin levels in the house dust from the current study to those in other peer-reviewed studies, for both agricultural and non-agricultural study populations..

1.2.5 Major Contributions of Dissertation

Chapter 8 provides a conclusion of this dissertation, focusing on the major contributions this research has brought to the fields of environmental and public health and discusses practical future works. The Chapter additionally highlights this study's limitations, lessons learned, and future directions.

1.3 Background

1.3.1 Overview of Pesticides

Pesticide products are substances that contain at least one active ingredient to control pests in the environment (USEPA, 2014a). Pesticides are numerous and diverse, and many attempts have been made to place them into distinct categories.

Often times, pesticides are categorized according to the type of pests they target. For instance, insecticides are a type of pesticide that target insects and arthropods, such as ants or cockroaches, whether in homes, restaurants, schools, or agricultural fields. On the other hand, herbicides are those that target weeds to so that fields, roads, or other areas that could otherwise become overgrown may be cleared (USEPA, 2012b). An alternative method of categorization of pesticides is by a common chemical family and mode of action. For example, all organophosphate (OP) pesticides share the same general chemical structure and affect the nervous system by disrupting the neurotransmitter acetylcholine, while pyrethroids are all a synthesized version of a natural pesticide that is derived from the extract of the chrysanthemum flower and can interact with the nervous system (USEPA, 2014a).

Although pesticides are wide-ranging, almost all pesticides have the same intended purpose of preventing, destroying, repelling, or mitigating a pest or preventing plant growth (ibid). Given that the intrinsic purpose of most pesticides is literally to harm or kill its target, the impacts of pesticide exposure on human health, as well as to the environment, are naturally of great concern (Wilson, 2001). Despite these concerns, many argue that pesticides are necessary because they are so effective at controlling pests, such as weeds, fungus, insects, parasites, and rodents, and because pesticides are often the only successful method of controlling such pests when outbreaks occur (USEPA, 2012b). As such, pesticides use is pervasive, both within the agricultural industry and among the general American population; resulting in widespread human exposure from many sources and multiple exposure routes (Crinnion, 2000; Kamel and Hoppin, 2004; Damalas and Eleftherohorinos, 2011).

1.3.2 Pesticide Exposure Sources and Routes

1.3.2.1 Workers' Occupational Exposure to Pesticides

Agricultural workers in open fields or orchards, those in the pesticide manufacturing industry, and exterminators of residential pests may all experience occupational pesticide exposure (Damalas and Eleftherohorinos, 2011), which can occur through inhalation, ingestion, and dermal absorption. It has been estimated that every year occupational pesticide exposure results in 18 cases of pesticide-related illness from acute pesticide poisonings for every 100,000 workers in the United States (Calvert et al., 2004). In addition, studies in the peer-reviewed literature have long reported associations between chronic occupational exposure to pesticides and a wide range of serious health effects, including Parkinson's disease (Semchuck, 1992), reproductive and developmental disorders (Padungtod et al., 2000; Hanke and Jurewicz, 2004), cancer (Van Maele-Fabry et al., 2007; Karami et al., 2008), and decreased lung function (De Jong et al, 2014).

There are only two primary federal laws that regulate pesticide exposure in an occupational setting. First, the USEPA's Worker Protection Standard (WPS) requires that owners and employers of agricultural establishments provide: (1) pesticide safety training to workers and handlers, (1) protections from potential pesticide exposures (e.g., having restricted entry intervals following applications), and (3) mitigations in the case that pesticide exposure does occur (e.g., having decontamination supplies on hand) (USEPA: 2015e; USEPA, 2016a). Second, the Occupational Safety and Health Administration's (OSHA) Field Sanitation and Temporary Labor Camps Standards require that all temporary labor camps have potable drinking water, and toilet and hand washing facilities available (OSHA, 2016).

However, despite these Standards, farms employing less than 11 workers are not required to comply with the prescribed health and safety requirements. This exempts up to 88% of all farms in the United States from inspections, resulting in 33% of all farmworkers not being protected by these Standards (UFW, 2011). Furthermore, many workers have been prevented from organizing and joining unions that could provide protection due to the exclusion of agricultural workers from the National Labor Relations Act (UFW, 2011). These exclusions are counterproductive to protecting workers from occupational pesticide exposure.

1.3.2.2 General Population's Exposure to Residential Use Pesticides

Pesticide exposure in the general population can occur by means of residential pesticide use in and around the home (WHO, 1997; Grossman et al., 1995; Bradman and Whyatt, 2005). This primarily occurs through inhalation of indoor air or ingestion of house dust. In the studies contained in the peer-reviewed literature, low-income urban families are often the focus of residential pesticide use since this population is usually subjected to poor housing conditions that promote pest infestations, thereby motivating these families to apply residential pesticides (Gurunthan et al., 1998; Kitch et al., 2002; Whyatt et al., 2002; Rudel et al., 2003; HUD, 2006; Julien et al., 2008; Adamkiewicz et al., 2011; Morgan et al., 2012). For example, low socio-economic status homes often have structural deficiencies, such as holes (Adamkiewicz et al., 2011) which could increase the likelihood of pests entering the home. Previous studies have long reported an association between residential pesticide use and cancer (Gold et al., 1979; Reeves et al., 1981; Lowengard et al., 1987; Leiss et al., 1995; Turner et al., 2011) More recently, an association with delays in early childhood neurodevelopment has also been reported (Lovasi et al., 2011).

Under the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the USEPA differentiates between general use pesticides (i.e., those available for the general public) and restricted use pesticides (i.e., those not available for use or purchase by the general public, due to their higher potential to negatively impact health or the environment) (USEPA, 2016b). While there are certain regulations for restricted use pesticides, general use pesticides have no federal regulatory requirements regarding residential pesticide applications, other than providing label instructions (Fenske et al., 1990). Given that residential pesticide applications occur within the privacy of the home, it is often difficult to acquire information about this type of pesticide use, and almost all studies in the peer-reviewed literature relied, at least partially, on self-reported data (Bradman et al., 1997; Adgate et al., 2000; Bass et al., 2001; Hartge et al., 2005; Colt et al., 2006). The minimal regulations related to residential pesticide use, combined with the difficulty of ascertaining information about household practices, causes residential pesticide use to be concerning, yet under-characterized.

1.3.2.3 General Population's Dietary Exposure to Pesticides in Food and Drink

It is widely acknowledged that the primary source of pesticide exposure to the general population, particularly infants and children, is from dietary ingestion of pesticide-contaminated food and drink items (Wilson et al., 2003; Bouvier et al., 2005; Lu et al., 2008; Damalas and Eleftherohorinos, 2011). The USEPA is responsible for establishing a pesticide tolerance level (i.e., maximum pesticide residue level permitted) in foods, which is specific to the combination of crop and pesticide (Winter, 1992). Under the Food Quality Protection Act (FQPA) of 1996, pesticide tolerance levels in foods are supposed to be set at a level of "a reasonable certainty of no harm" based on a risk assessment process (USEPA, 2015a).

Substantial efforts have been put forth to better characterize consumers' exposure to pesticide residues from dietary ingestion. For example, the Food and Drug Administration's (FDA) Total Diet Study is an ongoing initiative to sample for pesticides each year in hundreds of foods that are common in the typical American diet (FDA, 2010). Interestingly, the most commonly detected pesticide residue in 2008 was DDT (22%) even though this pesticide was banned in the United States in 1972 (ATSDR, 2003; FDA, 2010). In addition, the United States Department of Agriculture's (USDA) Pesticide Data Program (PDP) collects data on levels of pesticide residues in a wide-variety of foods that vary from year to year (PDP, 2007). In 2006, the PDP reported spinach, summer squash, and peaches all had over 90% detectable residue rates; however, pesticide residues that exceeded the pesticide tolerance levels were detected in only 0.2% of the samples (n=12,554) (ibid).

Reporting on associations between dietary exposure to pesticides and adverse health outcomes has been both sparse and conflicting (Dougherty et al., 2000; Curl et al., 2003; Winter and Katz, 2011). In Dougherty et al., (2000), the authors reported that childhood daily dietary ingestion exposure to the pesticides chlordane, DDT, and dieldrin exceeded the one-in-one million cancer benchmark. In addition, the non-cancer benchmarks were exceeded for chlordane, dieldrin, and methamidophos. On the other hand, a study that used probabilistic techniques to estimate the dietary exposure of consumers to fruits and vegetables that were previously characterized as commodities with high levels of pesticide residues reported that all exposures posed negligible risks (Winter and Katz, 2011). Curl et al. (2003) reported that the estimated daily dose of some pesticides (e.g., oxydemeton-methyl) exceeded benchmark levels for non-cancerous health outcomes, while the estimated daily dose of other pesticides (e.g., malathion) did not exceed the benchmark.

1.3.2.4 Pre-Natal Exposure to Pesticides

Pre-natal exposure to agricultural pesticides, which can be a result of the parents' occupational, dietary, or residential exposure, is also a concern, and it has been associated with serious health effects in infants, toddlers, and children (Rohlman et al., 2005; Eskenazi et al., 2007; Wigle et al., 2009). For example, pre-natal maternal exposure to occupational pesticides has been strongly and consistently associated with childhood cancers, including leukemia (Wigle et al., 2009) and brain cancer (Kuijten et al., 1992; van Winjingaarden et al., 2003; Shim et al., 2009). However, other studies found no significant risk of childhood brain cancer from parental pesticide exposure during pregnancy (Bunin et al., 1994; Leiss and Savitz, 1995). Neurological, intellectual, and behavioral issues in infants, toddlers, and children, associated with pre-natal exposure to organophosphate pesticides, have been reported by epidemiological studies (Engel et al., 2007; Rohlman et al., 2005) as well as a major birth cohort study of Latino farmworker families from the Center of Health Assessment of Mothers and Children of Salinas (CHAMACOS) study (Eskenazi et al., 2007). Finally, the risk for autism spectrum disorders has been positively associated with residential proximity to organochloride pesticide applications which occurred around the period of central nervous system embryogenesis (Roberts et al., 2007).

1.3.3 Aggregate and Cumulative Exposures to Pesticides

When each type of pesticide exposures is considered independently, the level of risk for adverse health outcomes could potentially appear minimal. However, the combination of chronic pesticide exposures from various sources, via multiple exposure routes, and with an additive toxic effect of multiple pesticides with similar toxicological properties, could result in an unacceptable level of risk for adverse health outcomes. As such, in order to improve the characterization of pesticide exposures, and its associated health risks, it is crucial to consider the individual’s aggregate and cumulative exposure to pesticides. Aggregate exposures incorporate all the different sources of pesticide exposure, including those from occupational sources, along with non-occupational sources, such as food and drink, and from residential use of pesticides. Cumulative exposure incorporates the additivity of doses from multiple pesticides that have the same mechanism of toxicity (USEPA, 2015c).

The landmark legislation in the United States that acknowledges the need for incorporation of aggregate and cumulative pesticide exposures is the Food Quality Protection Act (FQPA) of 1996, which mandates that aggregate and cumulative exposures must be considered when setting agricultural pesticide tolerance levels in food commodities (USEPA, 2015a). Based upon aggregate and cumulative risk assessments, these pesticide tolerance levels in food should be set at a level of "a reasonable certainty of no harm." Sources of pesticide exposure to the general public that are considered for these risk assessments are through the diet and residential pesticide use. However, potential occupational exposures are not included for these risk assessments.

1.3.4 An Additional Concern: Residential Exposure of Agricultural Pesticides Transported into the Home

For those living in agricultural communities, and most notably for farmworkers and their families, the transport of agricultural pesticides away from agricultural fields and into homes is an additional source of potential pesticide exposure (Rawlings et al., 1998; Anderson et al., 2000; Faustman et al., 2000; Eskenazi et al., 2007). Unfortunately, current risk-assessments under FQPA 1996 do not incorporate residential pesticide exposure in the home that originates from agricultural pesticides transported away from fields. Therefore, such risk assessments may underestimate the total risk associated with residential pesticide exposure for those living in agricultural communities, especially for farmworkers and their families who may also experience occupational and para-occupational pesticide exposures. In order to better characterize overall exposures of those living in agricultural communities, particularly farmworkers and their families; it is first necessary to better understand the transport pathways of pesticides from agricultural fields into homes.

1.3.5 Limited Success in Previous Interventions of the Take-Home/Soil Track-in Pathway

It has been well documented in the peer-reviewed literature that agricultural pesticides detected in farmworkers' homes could, to some extent, be attributed to the take-home/soil track-in pathway (Eskenazi et al., 1999; Faustman et al., 2000; Lu et al., 2000; Curl et al., 2002; McCauley et al., 2003; Thompson et al., 2003; Curwin et al., 2005; Coronado et al., 2006; Lozier et al., 2012). For example, the concentration of agricultural pesticides in house dust has been found to be higher for agricultural families compared to non-agricultural families as a function of closer distance to agricultural fields (Lu et al., 2000). Pesticide concentrations in farmworkers' homes have also been correlated with pesticide concentrations in their vehicles (Curl et al., 2002). Additionally, the types of pesticides detected in the urine of farmworkers' children were found to match the pesticides to which their parents were exposed in the field (Coronado et al., 2006). Finally, a strong positive correlation has been seen between the number of farmworkers in the home and the concentration of agricultural pesticide residues found in house dust (McCauley et al., 2001).

In response to the evidence of the relevance of the take-home/soil track-in pathway, several interventions have been implemented that aimed to modify farmworkers' behaviors that related to this pathway (Thompson et al., 2008; Arcury et al., 2009; Bradman et al., 2009; Salvatore et al., 2009; Strong et al., 2009). However, none of these interventions demonstrated a reduction in the farmworkers' in-home agricultural pesticide levels. One intervention study in North Carolina and Virginia sought to educate women from Latino farmworker families on pesticide safety, through the use of promotoras (i.e., community health workers) (Arcury et al., 2009). Results of that study indicated that while participants in the intervention reported that they had received pesticide education and could recognize key messages, their knowledge regarding pesticide exposures and related behaviors did not change. It was posited that a more thorough and structured educational program may be necessary to adequately address the educational and cultural characteristics of the study population. This intervention did not include any biological or environmental sampling to assess changes in pesticide levels after the intervention.

Similarly, a worksite intervention was previously implemented among strawberry harvesters in California (Bradman et al., 2009; Salvatore et al., 2009). This intervention consisted of providing the farmworkers with: education about agricultural pesticide safety; warm water and soap to allow for convenient hand washing; and coveralls and gloves that could be worn while working and removed prior to going home. Self-reported behavioral results indicated that some "at-work" behaviors, including using gloves and washing hands at certain break times and before going home, improved after the intervention. However, "after work" behaviors, that required storing work shoes outside the home, changing work clothes within 15 minutes of arriving home, and storing work clothes separately, did not improve. After the intervention, the workers' urine, hand rinses, clothing, and skin samples were tested for levels of malathion, a pesticide used while working in the field. Loading of malathion on the hands, and in the urine, were lower for those who wore gloves versus those who did not wear them. Also, while malathion was detected in clothing samples, it was not detected on skin samples, indicating that the clothing acted as a protective barrier against dermal contact with agricultural pesticides. This intervention did not include samples before the intervention or from any environmental media at the home.

Finally, as mentioned earlier, the Para Niños Saludables intervention educated entire agricultural communities in Washington State about agricultural pesticide safety practices related to the take-home pathway (Thompson et al., 2008; Strong et al., 2009). This intervention study consisted of conducting a baseline survey of a cross-sectional sample of farmworkers in 24 communities, which were subsequently randomized into control and intervention groups. Prior to the intervention, agricultural pesticide levels in dust from farmworkers' homes and vehicles, along with in their children's urine, were measured (year one). For two years (years two and three), messages about agricultural pesticide safety were spread throughout the intervention communities through health fairs, puppet shows for children, block parties, community festivals, and widespread local media messages. Post-intervention, a new cross-sectional sample of farmworkers from the communities was evaluated by sampling house dust, vehicle dust, and children's urine once again (year four). The intervention successfully increased the number of farmworkers who took their shoes off before entering the home and changed out of work clothes within one hour of arriving home, but, there was still no significant difference found in agricultural pesticide residues in the house dust or in the urinary pesticide metabolite levels of the farmworkers or their children when compared to baseline measurements (Thompson et al., 2008; Strong et al., 2009).

The authors of Para Niños Saludables put forth multiple potential reasons for the limited effectiveness of their intervention. These included: changes to rulings by the USEPA that could have shifted agricultural pesticide use patterns; varied timing of pesticide sprayings from year to year; changes in climate or pests that could have increased agricultural pesticide applications; and natural variability in metabolic efficiencies among participants (relevant only to urine samples) (ibid). However, an additional possible reason for the lack of effectiveness could be that the study focused only on the take-home/soil track-in pathway and did not incorporate factors related to the air infiltration pathway, which may have been the more prominent pathway of agricultural pesticides into the homes.

1.3.6 Evidence of an Air Infiltration Pathway

There is reason to believe that the air infiltration pathway may be of significant relevance to pesticide transport from agricultural fields into farmworkers' homes. Robust evidence for long-range transport of agricultural pesticides through ambient air has existed for many years (Cohen and Pinkerton, 1966; Wadleigh, 1968; Bidleman and Olney, 1975; El-Shobokshy and Hussein, 1988). In addition, many previous studies have reported that residential proximity to an agricultural field or orchard was positively associated with pesticide levels in the home, which suggests that the transport of agricultural pesticides may be through the air (Simcox et al., 1995; McCauley et al., 2001; Quandt et al., 2004; Weppner et al., 2006; Coronado et al., 2011; Gunier et al., 2011; Deziel et al., 2013). In a Washington State study, the pesticide methamidophos was measured using active air sampling to capture the vapor phase and passive sampling, using deposition plates, to capture the particle phase (Weppner et al., 2006). In that study, methamidophos was detected in the ambient air and on outdoor surfaces of the community after a known aerial application in a nearby field; confirming that drift had occurred. However, methamidophos was not detected inside homes, suggesting a lack of air infiltration (ibid). This is contrary to the findings of a study in an Arkansas agricultural community, where the pesticide propanil was measured, also using a combination of active sampling to capture the vapor phase and passive sampling, using deposition plates, to capture the particle phase (Richards et al., 2001). That study detected almost no propanil vapors from active sampling, yet there were detectable levels of the pesticide on surfaces inside some of the homes, which were consistent with the wind direction from the field to the homes. The results of Richards et al. (2001) suggest that air infiltration of propanil in the particle-phase did occur. Although air infiltration may be an important pathway of pesticides into the home, there has been little focus on intervening along this pathway.

1.3.7 House Dust as a Media of Interest

The current study chose to use farmworkers' house dust as the media of interest with respect to assessing agriculture pesticide levels in the home. House dust is defined as a mixture of particulate matter, coming from settled indoor air particles, as well as soil tracked into the home, along with organic matter sources that are biologically derived, such as fungal spores, animal dander, and skin cells (Morawska, 2006). Since house dust can cause contaminants to be trapped and preserved, this media offers a sample of long-term accumulation (ibid). With a variety of sources contributing to house dust, along with the combination of inorganic and organic particles of various sizes, this media can reveal much information about potential exposures to contaminants in the home. Please see Figure 1-1 for a visual conceptualization of the contributions to house dust.

Previous studies have determined that semi-volatile organic compounds can accumulate in house dust, thereby increasing the risk of pesticide exposure through non-dietary ingestion (Butte and Heinzow, 2002; Jones-Otazo et al., 2005; Webster et al., 2005; Gevao et al., 2006; Wu et al., 2007; Weschler et al., 2008; Bonvallot et al., 2010; Xing et al., 2011). Several studies have reported that non-dietary ingestion is quantitatively the more significant route of exposure in residential settings compared to inhalation (Jones-Otazo et al., 2005; Webster et al., 2005; Gevao et al., 2006; Wu et al., 2007; Xing et al., 2011; Zartarian et al., 2012). House dust, as a reservoir for agriculture pesticides in particular, has been explored frequently over the past 15 years, with studies detecting a wide-range of agricultural pesticides in this media (Lu et al., 2000; McCauley et al., 2001; Curl et al., 2002; Fenske et al., 2002; Lu et al., 2004; Beamer et al., 2007). Non-dietary ingestion of agricultural pesticides has been specifically reported as a major contributor to overall pesticide exposure (Beamer et al., 2009a; Beamer et al., 2009b).

1.3.8 A Special Concern: Children's Health Related to Non-Dietary Ingestion of Pesticides

It is important to note that children have a dependency on adults to ensure a safe and healthy environment (USEPA, 2015b). Therefore, it is important that the home where the child spends many hours, and which is assumed to be a safe haven for the entire family, is not an environment that puts the child at risk for serious health effects. Research initiatives, such as those cited in this dissertation, offer a step forward in improving the health and safety of farmworkers' children in their homes. However, much is left to be done.

Non-dietary ingestion exposure to pesticides in house dust is particularly concerning for children. The relevance of this concern is recognized at the federal level in FQPA 1996, which provides special consideration for infants and children in the pesticide risk assessment process (USEPA, 2015a). In fact, much of the peer-reviewed research contributing to the body of literature regarding non-dietary ingestion exposures to pesticides in children was done in response to the directive of the FQPA 1996 (Buck et al., 2000; Zartarian et al., 2000; Fenske et al., 2002; Hore et al., 2006; Bradman et al., 2007; Zartarian, 2012; Beamer et al., 2012a). Researchers in the field of children's health unanimously agree that it is important to realize that children are not "little adults" and as such, understanding children's exposures are distinct from that of adults (USEPA, 2015b).

One major way in which children differ from adults is their unique behaviors that can lead to increased non-dietary ingestion of pesticide-contaminated house dust. A higher frequency of hand-to-object-to-mouth and hand-to-mouth contact in young children, which generally decreases with age, has been well established in the peer-reviewed literature (Lourie et al., 1963; Baltrop, 1966; Zartarian et al., 1997; Zartarian et al., 1998; Cohen Hubal et al., 2000; Tulve et al., 2002; Beamer, 2007; Beamer et al., 2008; Beamer et al., 2009b). The placing of objects and hands in one's mouth is considered to be a normal behavior related to the development of young children for reasons such as exploring their surrounding world and relieving pain from teething (Ruff et al., 1984; Groot et al., 1998; Cohen Hubal, 2000). Given that children also tend to spend more time on the floor crawling around and playing with toys and other objects (Tulve et al., 2002), the ingestion of house dust during these hand-to-object-to-mouth and hand-to-mouth contact behaviors is naturally higher than that of an adult.

Another way in which children are different from adults is the fact that they have stark physiological differences that result in an increased susceptibility to health effects from pesticide exposure, especially during certain developmental stages, such as fetal development and puberty (USEPA, 2015b). Among the many physiological differences between children and adults include lower body weights, increased surface area-to-volume ratios, and less developed immune systems and nervous systems (Eskenazi et al., 1999; Cohen Hubal et al., 2000; Faustman et al., 2000;

USEPA, 2015b). As such, children tend to have a higher rate of absorption across their intestines, thereby increasing the actual dose of pesticides per unit consumed when compared to adults (Arcury et al., 2007). Also, children's bodies are less capable of detoxifying pesticides compared to adults, and, thus the likelihood of experiencing adverse health effects from pesticide exposure is higher for children (ibid). Pre-natal exposure to pesticides is an additional concern as this exposure has been associated health effects in infants and children, including behavioral issues and developmental delays (Eskenazi et al., 2004; Young et al., 2005; Eskenazi et al., 2007; Lizardi et al., 2008).

1.3.9 Residence Time of Agricultural Pesticides in House Dust

Given the concern of pesticide exposure through non-dietary ingestion of house dust, estimating the residence time (i.e., time of persistence) of pesticides in the house dust is a worthwhile endeavor. There is reason to believe that the residence time of pesticides in house dust could less than one year, which is one of the hypotheses of this dissertation. The reporting of residence time in floor particles has ranged in the peer-reviewed literature (Allott et al., 1994; Qian et al., 2008; Layton and Beamer, 2009; Shin et al., 2013). In a single house that was vacuumed on a daily basis, the residence time of particles in the house dust was reported to be 29 days (Allott et al., 1994). In the Southern Arizona application of the previously described soil contaminant transport model, the residence time of particles in the floor dust was estimated to be 61 days (Layton and Beamer, 2009). Similarly, in Qian et al. (2008), the residence time was estimated to be 85 days in homes that were vacuumed once per week, although the authors also suggested that this could vary drastically based on vacuuming efficiency. On the other hand, in Shin et al. (2013), the residence time for permethrin at steady-state was estimated to be 3.9 years. In that study, it was assumed that complete removal of pesticides from carpets would be very difficult compared to removal from hard floors, significantly increasing the residence time. It would be a significant contribution to better understand the realistic residence times of agricultural pesticides so that future intervention studies are able to choose a reasonable time period between baseline and follow-up testing.

CHAPTER 2

SAMPLING FARMWORKERS' YARD SOIL, OUTDOOR AIR, AND HOUSE DUST FOR AGRICULTURAL PESTICIDES IN YUMA COUNTY, ARIZONA

2.1 Introduction

2.1.1 Collecting Environmental Samples and Asking the Right Scientific Question

One of the most common primary scientific tools used to evaluate environmental health issues, such as pesticide levels in communities, is direct collection of environmental samples in a field study (Aral, 2010). Direct sample collection is indispensable when attempting to establish whether, and to what extent, pesticide levels exist in the environment that could lead to health outcomes in exposed populations. Although field sampling is of great value for understanding environmental health issues, it is also undoubtedly costly, time-consuming, and resource intensive. For these reasons, it is crucial that researchers put great care into ensuring that the right scientific question is being asked before sampling, and that a strategic sampling and analysis plan is developed accordingly.

Asking the right scientific question is not an elementary task, and the failure to do so is one of the primary factors behind many current environmental issues (Fowler and Hobbs, 2009). The scientific method, which is the world-wide accepted process used to address scientific issues and conduct studies, is embedded in ensuring that the right scientific question is asked. The way in which a researcher asks a question is at the heart of how he or she searches for the answer (Ross, 2003). A scientifically sound hypothesis must lead to a well thought-out sampling and analysis design which plays a fundamental role in ensuring that data collected are able to sufficiently address the scientific questions at hand. It is only through this careful approach that it becomes possible to collect appropriate and defensible data that truly represent the reality of the situation (USEPA, 2002a).

2.1.2 Targeting Relevant Pesticides in Environmental Samples

The vastness of agricultural pesticide use throughout the United States has made pesticides an issue of nation-wide concern. Over 1.1 billion pounds of active ingredient of pesticides have been applied annually throughout the United States since the 1980s (Levine, 2007; USEPA, 2011b), and approximately 850 million pounds of those pesticides are categorized as "conventional pesticides" used for agricultural purposes ("other pesticides" include wood preservatives, specialty biocides, and chlorine/hypochlorites used in water treatment) (ibid). In the quest to determine pesticide levels in environmental samples taken at farmworkers' homes, one of the most important, yet difficult, decisions to make is which pesticides should be targeted.

Nationwide, the most highly applied pesticides used for agricultural purposes in 2007 (the most up-to-date national statistic available) were glyphosate, atrazine, metam-sodium, and metalachlor-s, although the pesticides of highest use can surely change from year to year (USEPA, 2011b). Yet, these national-level statistics may be of little relevance to a specific agricultural community of interest. Agricultural pesticide use occurs in response to the specific needs of that area, including desired crops, relevant pests, soil content, and climate conditions. With over 17,000 pesticide products registered in the United States as of 2007 (Levine, 2007), it is doubtful that the pesticides of greatest concern for any given agricultural community of interest would be the same as those reported in an aggregated nationwide statistic.

As such, prior to field sampling in an agricultural community, it is crucial to implement a systematic method to identify, and subsequently target, the most relevant pesticides in that community. Without first asking the question of which pesticides are most relevant in the community of interest, it is impossible to ultimately address whether the levels of such pesticides in the environment are of concern to the community's health.

2.1.3 Prioritizing Pesticides in a Community by Using a Hazard Ranking System

The use of hazard ranking systems to prioritize environmental contaminants that are of greatest risk to human health is a long-standing respectable method to guide field sampling and contaminant analysis (USEPA, 1992; Mitchell et al., 2002; Baun et al., 2006; Dix et al., 2007). In order to guide the field sampling of the current project, and prioritize pesticides of greatest health concern, a pesticide hazard ranking system previously developed by Ms. Sugeng was applied in the agricultural community of interest for this project, Yuma County, Arizona (Sugeng, 2012; Sugeng et al., 2013).

This pesticide hazard ranking system considered the pounds of pesticide application in Yuma County, the associations of the pesticides with various chronic health effects (i.e., cancer, endocrine disruption, developmental/reproductive toxicity, and a combination of these three prior chronic health effects), and the exposure potential to the pesticide based on intrinsic chemical characteristics (e.g., soil half-life, vapor pressure). These variables were used to compute hazard factors, which were then used to adjust the actual/raw pesticide applications, so that hazard potential is taken into consideration. Pesticides were prioritized according to their ranked "hazard-adjusted" pesticide application. Details on the development and implementation of this hazard ranking system are currently published (Sugeng, 2012; Sugeng et al., 2013).

2.1.4 Focusing on Yuma County, Arizona as the Agricultural Community of Interest

Yuma County, Arizona is an agricultural community that has long necessitated additional field sampling to examine the presence of pesticide hazards. Agriculture is the cornerstone of Yuma County's economy, generating three billion dollars in economic activity in 2010 and employing up to 20,200 workers during the peak season (YCDDS, 2015). Yuma County is also known as the "winter vegetable capital of the world," producing approximately 90% of the leafy vegetables grown in the United States during the months of November to March (YCDDS, 2015; Yuma Visitors Bureau, 2015). In Yuma County, pesticide application is confined to 335 square miles of designated farmland, which is only approximately 6% of the County's total land (NASS, 2014). Of great concern is the fact that the average distance between homes and agricultural fields is 433 feet (0.08 miles) (CDC, 2002), which increases the likelihood of agricultural pesticides being transported and entering nearby homes, thereby increasing exposure risks to families.

Despite the evident high prevalence of pesticide use and increased risk to families living in Yuma County communities, sampling for pesticides in the environment had not been conducted in this community since 2000 (Robertson et al., 1999; O'Rourke et al., 2000; CDC, 2002; Thompson et al., 2005). The current study sought to address this need for additional field sampling in Yuma County, utilizing the previously described pesticide hazard ranking system, applied specifically to this community, to guide the pesticide analysis.

2.2 Methods

2.2.1 Study Overview

Twenty-one farmworker families were recruited to participate in this study. Yard soil, outdoor air, and indoor house dust samples were collected from each home. Additionally, a questionnaire was administered to at least one adult in each home, which is further discussed in Chapter 5.

2.2.2 Participant Selection and Recruitment

Participants in this study were limited to families with at least one farmworker who was at least 18 years old and living in Yuma County, Arizona, within 3 miles of an agricultural field. A local non-profit community health organization that serves farmworkers and other residents of Yuma County, Campesinos sin Fronteras, assisted in the identification and recruitment of 21 farmworker households to participate in this study. The Human Subjects Protections Program at the University of Arizona approved all relevant protocols. Informed consent was obtained from at least one adult in each household prior to engaging in any study procedures. Household visits were conducted from March 2011 to February 2012. The entirety of the study population self-identified as Mexican/Latino/Hispanic and most families predominantly spoke Spanish; therefore, at least one bilingual researcher (English and Spanish) was present at all home visits and all study materials were made available in both languages.

2.2.3 Yard Soil Sample Collection

Soil samples were collected from each farmworker's yard, totaling 23 soil samples, including two duplicates. A sample of at least five grams was collected outside of the most commonly used entrance way. If there was a defined walkway, a sample was taken by sweeping along the path. If there was no clear walkway, the participant(s) was/were asked about the general path in which the family walked along from the road to the house, and then the top layer of soil along that path was collected by sweeping. A tape measure was used to measure each area sampled. The bristles of the broom were wiped down with isopropyl alcohol between homes for decontamination purposes.

2.2.4 *House Dust Sample Collection*

House dust samples were collected from each farmworker's home, totaling 23 dust samples, including two duplicates. A Hoover vacuum with an altered inlet containing a Teflon-coated and fiberglass filter was used for house dust collection (Gordon et al., 1999). The samples were preferentially taken from the most commonly used room of the house, as identified by the participant(s). A sample of at least two grams of dust was obtained from the home, and the area sampled was measured using a tape measure. If two grams of dust could not be obtained from vacuuming the floor, then curtains, windowsills, or couches were additionally sampled. The vacuum inlet was wiped down with isopropyl alcohol between homes for decontamination purposes.

2.2.5 Outdoor Air Sample Collection

Outdoor air samples were collected from each farmworker's home yard, totaling twenty-five air samples, including 2 blanks and 2 duplicates. Sampling occurred for 48 hours using an SKC air pump and low volume polyurethane foam (PUF) cartridge packed with XAD-2 resin at a flow rate of 4 L/minute, based on USEPA Method TO-10A (USEPA, 1999). The air pump was calibrated before and after sampling with a Bios Defender Primary Flow Calibrator (Mesa Labs, 2015). The temperature and relative humidity were also measured using the Calibrator before and after sampling.

2.2.6 Sample Processing

Upon completion of the sampling, the outdoor air, yard soil, and house dust samples were stored on ice, in the dark, until they could be transported back to the laboratory, where they were then stored in a freezer at -29 degrees Celsius. All soil and dust samples were sieved to <63 μm since this size fraction has been shown to preferentially adhere to shoes, promoting track-in to the home, and is more likely to be resuspended by the wind, promoting air infiltration to the indoor environment

(Layton and Beamer, 2009). It has also been shown that the majority of particles that adhere to hands is <63 μm (Choate et al., 2006), increasing the likelihood of pesticide exposure through hand-to-mouth contact. The smaller size fraction has further been demonstrated to have a higher concentration of contaminants as compared to larger size fractions (Bright et al., 2006; Spalt et al., 2009; Beamer et al., 2012b).

2.2.7 Decisions Related to Pesticide Analysis

The decision regarding which pesticides to target in the yard soil, outdoor air, and house dust samples was based on the results of the hazard ranking system as applied to Yuma County in combination with the selected laboratory's capability to analyze for a suite of pesticides under a single method. The highest ranked pesticides for overall chronic health effects in Yuma County, Arizona were given the top priority for analysis. These prioritized pesticides were presented to chemists at Battelle Memorial Institute, the leading research institution for pesticide analysis in the United States, located in Columbus, Ohio. The chemists at Battelle Memorial Institute determined that, among the prioritized pesticides, the following could be successfully analyzed as a single suite using one method: bifenthrin, endosulfan, cis/trans-permethrin, pronamide, and trifluralin. DDT was additionally included in the suite because a previous study detected it in some California farmworkers' homes in 2002, despite having been banned in 1972 in the United States (Bradman et al., 2007). The full listing of top ranked pesticides for individual health effects and combined chronic health effects, along with delineation of laboratory capability to analyze, and the final decision for pesticide analysis can be viewed in Table 2-1.

Table 2-1: Pesticides Chosen for Analysis Based on Hazard Ranking Results and Laboratory Capabilities

Top Ranked Pesticides Based on Hazard Ranking Results				**Lab Able to Analyze Combined Ranking Pesticide?**	**Final List for Pesticide Analysis**
Carcinogens	**Endocrine Disruptors**	**Reproductive/ Developmental Toxicants**	**Combined Ranking**		
Metam-sodium	Trifluralin	Maneb	Maneb	No	Bifenthrin
Maneb	Bensulide	Metam-sodium	Metam-sodium	No	Carbaryl
Pronamide	Maneb	Bifenthrin	Trifluralin	Yes	DDT
Mineral Oil	Endosulfan	Carbaryl	Pronamide	Yes	Endosulfan
Permethrin	Chlorpyrifos	Bromoxynil octanoate	Bifenthrin	Yes	Permethrin (cis/trans)
Iprodione	Metam-sodium	EPTC	Bensulide	Yes	Pronamide
Bifenthrin	Pronamide	Streptomycin sesquisulfate	Mineral Oil	No	Trifluralin
Cypermethrin	DCPA		Endosulfan	Yes	
Trifluralin	Cypermethrin		Carbaryl	Yes	
1,3-Di-chloropropene	Pendimethalin		Permethrin	Yes	

2.2.8 Pesticide Analysis

The <63 μm size fraction of soil and dust samples, along with the outdoor air samples, were sent to Battelle Memorial Institute for pesticide analysis. Prior to extraction, matrices were spiked with Carbaryl-$^{13}C_6$ and trans-Permethrin-$^{13}C_6$ surrogate recovery standards, and a 7-point calibration curve was prepared. The soil and air samples were analyzed using an accelerated solvent extraction with 1:1 hexane:acetone. Dust samples were analyzed with a sonication extraction method with 1:1 hexane:acetone. A portion of each soil, air, and dust sample were passed through an aminopropyl solid phase extraction column. The extract was concentrated to one milliliter, analyzed via gas chromatography/mass spectrometry (GC/MS), and plotted using the calibration curve.

2.2.9 Data Analysis

Samples with non-detectable pesticide concentrations were indicated as a non-detectable (ND). For the purposes of statistical analyses, all ND concentrations were replaced with the minimum detection limit (MDL)/√2. This method was chosen because it has been shown to provide accurate estimates when up to half of the samples are non-detectable among data with low-to-moderate variability (Hornung and Reed, 1990).

Some pesticide concentrations were detected despite falling below the MDL. According to the Analytical Methods Committee (1987), such values should be considered true estimates of concentrations, and it is recommended to maintain the observed value, rather than using replacement values, whenever statistical analyses will be performed using the dataset (ibid). As such, in the current study, all concentrations that fell below the MDL were reported using the observed value for all statistical analyses. Also, the detection frequency (DF) of each pesticide included the samples with reported concentrations below the MDL.

2.2.10 Associations between Detection Frequency and Raw/Actual Pesticide Application and Hazard-Adjusted Pesticide Application

As mentioned in the introduction section of this Chapter, the hazard ranking system used hazard factors to adjust the raw pounds of pesticide application, thereby calculating hazard-adjusted pesticide applications for each pesticide. As a means of assessing the hazard ranking effectiveness, Spearman's rank correlations were first performed between detection frequency in each media and the raw/actual pesticide application. Next, Spearman's rank correlations were performed between detection frequency in each media and the hazard-adjusted pesticide application. The Spearman's rank correlations for raw/actual pesticide application and hazard-adjusted pesticide application were then compared.

2.3 Results

2.3.1 Pesticide Sampling Results in Yard Soil, Outdoor Air, and House Dust

All pesticides, with the exception of DDT, were detected in at least one of the media types and in at least one home, although none were detected in every home. In house dust, trans-permethrin and cis-permethrin were the most commonly detected analytes (91% DF for both isomers) with concentrations ranging from ND to 3,192.60

ng/g and ND to 2,207.54 ng/g, respectively (Table 2-2). Bifenthrin was also commonly detected in house dust (38% DF), with concentrations from ND to 2,241.71 ng/g (Table 2-2).

A similar trend was observed in the yard soil, where the most commonly detected pesticide was again trans-permethrin (86% DF) with concentrations ranging from ND to 402.65 ng/g (Table 2-3), followed by cis-permethrin (67% DF) with a concentration range of ND to 302.87 ng/g. Bifenthrin was also commonly detected (39% DF) ranging from ND to 132.91 ng/g for the concentrations (Table 2-3).

A different trend was observed in the outdoor air, compared to that of house dust and yard soil. The most common pesticide detected in the outdoor air was trifluralin (95% DF), with a range in concentration of ND to 12.20 ng/m^3 (Table 2-4). Bifenthrin was the next most commonly detected pesticide in air (DF 43%), with concentrations ranging from ND to 3.84 ng/m^3, followed by trans-permethrin (DF 19%), with concentration ranging from ND to 1.30 ng/m^3 (Table 2-4).

Table 2-2: Description of Pesticides in House Dust (n=21)

Pesticide			**Concentration (ng/g)**				
	MDL	DF (%)	Min	25th %	50th %	75th %	Max
Bifenthrin	20	10 (48)	ND	ND	ND	200.29	2,241.71
Carbaryl	50	1 (5)	ND	ND	ND	ND	29.02
DDT	20	0 (0)	ND	ND	ND	ND	ND
Endosulfan	50	0 (0)	ND	ND	ND	ND	ND
cis-Permethrin	4	19 (91)	ND	169.86	233.15	535.64	2,207.54
trans-Permethrin	4	19 (91)	ND	237.92	292.56	360.47	3,192.60
Pronamide	50	1 (5)	ND	ND	ND	ND	87.69
Trifluralin	20	1 (5)	ND	ND	ND	ND	21.34

Table 2-3: Description of Pesticides in Yard Soil (n=21)

Pesticide	**Concentration (ng/g)**						
	MDL	DF (%)	Min	25^{th} %	50^{th} %	75^{th} %	Max
Bifenthrin	20	8 (38)	ND	ND	ND	23.74	132.91
Carbaryl	50	1 (5)	ND	ND	ND	ND	55.84
DDT	20	0 (0)	ND	ND	ND	ND	ND
Endosulfan	50	0 (0)	ND	ND	ND	ND	ND
cis-Permethrin	4	14 (67)	ND	ND	20.03	44.89	302.87
trans-Permethrin	4	18 (86)	ND	25.61	56.5	118.87	402.65
Pronamide	50	0 (0)	ND	ND	ND	ND	ND
Trifluralin	20	0 (0)	ND	ND	ND	ND	ND

Table 2-4: Description of Pesticides in Outdoor Air (n=21)

Pesticide	**Concentration (ng/m^3)**						
	MDL	DF (%)	Min	25^{th} %	50^{th} %	75^{th} %	Max
Bifenthrin	0.87	9 (43)	ND	ND	ND	0.56	3.84
Carbaryl	2.17	0 (0)	ND	ND	ND	ND	ND
DDT	0.87	0(0)	ND	ND	ND	ND	ND
Endosulfan	2.17	1 (5)	ND	ND	ND	ND	2.99
cis-Permethrin	0.17	1(5)	ND	ND	ND	ND	1.09
trans-Permethrin	0.17	4 (19)	ND	ND	ND	ND	1.3
Pronamide	2.17	0 (0)	ND	ND	ND	ND	ND
Trifluralin	0.87	20 (95)	ND	0.3	0.49	1.32	12.20

2.3.2 Correlations Between Pesticides in Yard Soil, Outdoor Air, and House Dust

For bifenthrin, concentrations in the yard soil and house dust were moderately correlated (r=0.36, p=0.15), along with between the yard soil and outdoor air (r=0.28, p=0.23). However, there was almost no correlation between outdoor air and house dust (r=0.004, p=0.99). Permethrin concentrations in yard soil and house dust were positively and moderately correlated (r= 0.33, p=0.15), although correlations with outdoor air could not be assessed due to low DF in this media. This analysis could not be done on the five remaining pesticides because of the numerous ND values. Correlations can be viewed in Table 2-5.

Table 2-5: Spearman's Correlation Matrix for Pesticide Concentrations in each Media (n=21)

Pesticide		*Air*	*Dust*
Bifenthrin	*Soil*	0.28	0.36
	Air	--	-0.004
Permethrin‡	*Soil*	.	0.33
	Air	--	.

‡cis and trans isomers combined;
.DF too low for statistical analysis

2.3.3 Correlations between Detection Frequency and Raw/Actual Pesticide Application and Hazard-Adjusted Pesticide Application

The Spearman's rank correlation computed between detection frequency (DF) in each media and raw/actual pesticide application can be seen in Table 2-6. The Spearman's rank correlation between DF in each media and the hazard-adjusted pesticide application can be seen in Table 2-7. The positive correlation for DF in outdoor air was slightly stronger with raw/actual pesticide applications (r=0.64, p=0.17) compared to the positive correlation with hazard-adjusted pesticide applications (r=0.52, p=0.28). For DF in soil, the correlation with raw/actual pesticide application was negative (r=-0.52, p=0.29), while the correlation with hazard-adjusted pesticide application was positive (r=0.70, p=0.12); the negative correlation with raw/actual pesticide application was weaker than the positive correlation with hazard-adjusted pesticide application. For DF in house dust, the negative correlation was weaker for the raw/actual pesticide application (r=-0.33, p=0.52) compared to the hazard-adjusted pesticide application (r=0.58, p=0.23).

Table 2-6: Spearman's Correlation Between Raw/Actual Pesticide Application (lbs) in Yuma County, Arizona from January 2006-June 2011 and Detection Frequency in Environmental Media (n=21)

Final List for Pesticide Analysis*	**Raw/Actual Pesticide Application (lbs)**	**Detection Frequency in Air**	**Detection Frequency in Soil**	**Detection Frequency in Dust**
Bifenthrin	991,214	43	38	48
Carbaryl	145,091	0	5	5
Endosulfan	456,596	5	0	0
Permethrin	141,575	19	86	91
Pronamide	281,931	0	0	5
Trifluralin	1,091,634	95	0	5
	Spearman's r (p-value)	*0.64 (p=0.17)*	*-0.52 (p=0.29)*	*-0.33 (p=0.52)*

*DDT removed because no application during study period

Table 2-7: Spearman's Correlation Between *Hazard-Adjusted* Pesticide Application (lbs) in Yuma County, Arizona from January 2006-June 2011 and Detection Frequency in Environmental Media (n=21)

Final List for Pesticide Analysis*	***Hazard-Adjusted* Pesticide Application (lbs)**	**Detection Frequency in Air**	**Detection Frequency in Soil**	**Detection Frequency in Dust**
Bifenthrin	826,012	43	38	48
Carbaryl	128,970	0	5	5
Endosulfan	1,623,452	5	0	0
Permethrin	125,845	19	86	91
Pronamide	751,816	0	0	5
Trifluralin	9,703,412	95	0	5
	Spearman's r (p-value)	*0.52 (p=0.28)*	*0.70 (p=0.12)*	*-0.58 (p=0.23)*

*DDT removed because no application during study period

2.4 Discussion

2.4.1 Overview

The current study successfully fulfilled the need to conduct updated sampling for pesticides in farmworkers' homes in Yuma County, Arizona. The fact that all pesticides selected were detected in at least one media for any given house, with the exception of DDT, suggests that agricultural pesticides may be transported from fields to homes in this community. With thousands of pesticides applied annually in Yuma County (Sugeng, 2012; Sugeng et al., 2013), the author of this study also made a significant effort to optimize the sampling by applying a pesticide hazard ranking system as a means to guide the pesticide analysis. Incorporation of this pesticide hazard ranking system prior to analyzing pesticides in outdoor air, yard soil, and house dust, samples at farmworkers' homes appeared to be effective at identifying relevant pesticide hazards specific to Yuma County, Arizona during the time period of sampling.

2.4.2 Differences in Detection Frequency by Pesticide

It was fortunate, and expected, that DDT was not detected in any of the homes for any of the media since this pesticide was banned in the United States in 1972, and the soil half-life of this pesticide should be no longer than 15 year (ATSDR, 2003). Since DDT was not applied agriculturally during the current study period, it was not identified as a pesticide hazard in the hazard ranking system, but it was nonetheless included in the analysis suite because it was previously detected in household dust and indoor air of a few California farmworkers' homes in 2002 (Bradman et al., 2007). One potential reason for the detection in those farmworkers' homes could be that DDT was being illegally imported from Mexico up until 2000, which is when it became completely banned in that country (Chanon et al., 2003). Since the community of interest in the current study is located directly along the U.S.-Mexico border, it was reasonable to include DDT in the analysis. It was reassuring to find that DDT was not detected in any of the sampled homes, and this may suggest that this pesticide is now of lesser concern in American agricultural communities and that any potential illegal import across the border in earlier years may have since ceased.

Bifenthrin and cis/trans-permethrin had high detection frequencies in all three media. These results imply that outdoor sources of bifenthrin and permethrin contribute to the indoor house dust levels of these pesticides. On the other hand, trifluralin was highly detected in the outdoor air, yet mainly undetected in both yard soil and house dust. The high detection frequency of trifluralin in the air directly outside of the homes (~95%) suggests that this pesticide would infiltrate through the air into the homes. One limitation of the current study is the fact that indoor air samples were not included, but it is logical that trifluralin would have also been detected in the indoor air. Trifluralin's higher volatility, which would cause the pesticide to remain largely in the vapor phase, is the probable cause of its lack of detection in the house dust.

Carbaryl, endosulfan, and pronamide each had very low detection frequencies in all three media, and they were mostly detected in the house dust. Since some chemicals may have a greater persistence indoors due to lack of degradation routes compared to outdoors (Egeghy et al., 2007), it is possible that these pesticides were also once detectable outdoors but had since broken down. It is also plausible that these low detection frequencies may reflect shortcomings of the hazard ranking system in being able to identify the most relevant pesticides for the particular environmental media being sampled. For example, pesticides with a high aqueous solubility may be primarily detected in ground water, which was not included for sampling in the current study, rather than in soil, air, or dust. A more thorough discussion of how chemical characteristics may influence detection in environmental media can be found in Chapter 4 of this dissertation.

2.4.3 Effectiveness of the Hazard Ranking System

To assess the effectiveness of using the hazard ranking system, the Spearman's correlation between each media, and the raw/actual pesticide application was compared to the Spearman's correlation between each media and the hazard-adjusted pesticide application. For yard soil and house dust, the Spearman's correlations were stronger for the hazard-adjusted pesticide application compared to with the raw pesticide application, suggesting that implementation of the hazard ranking scheme was useful for those media. It was particularly interesting to find that the detection frequency in soil was negatively correlated with the raw/actual pesticide application, yet positively correlated with the hazard-adjusted pesticide application. This highlights one of the strengths of the hazard ranking system, which is that pesticide hazard priorities are identified based on more factors than simply the amount to which the pesticide was applied in agricultural fields. On the other hand, for outdoor air, the Spearman's correlation was actually stronger for the raw pesticide application compared to the hazard-adjusted pesticide application. This may be due to the fact that outdoor air detection frequency is likely to be influenced by other factors, such as weather conditions during the sampling period and the inherent chemical characteristics of each specific pesticide. The potential effect of these factors on detection in environmental media is fully discussed in Chapter 4.

2.4.4 Comparison of Targeted Pesticides to Previous Studies

In order to compare the results of the current study to previous agricultural pesticide sampling studies, a literature review was performed to summarize the pesticides targeted for analysis and the overall results of those studies (Table 2-8). The cited studies included research initiatives to collect environmental samples from homes in an agricultural community (farmworker or general community member) that analyzed the samples for agricultural pesticides. Nineteen previous studies were identified, with sampling taking place in Arizona, California, Iowa, Oregon, and Washington. Three of these previous studies specifically occurred in Yuma County, Arizona, while the remaining 16 occurred in other states. Comparing the pesticides identified by the hazard ranking system to those targeted in the 19 previous agricultural pesticide sampling studies showed that, for the most part, the pesticides chosen for the current study were not among those analyzed in previous studies. Specifically, pronamide was not included in any of the previous studies. Bifenthrin, trifluralin, and endosulfan were each included in two of the previous studies. Permethrin and carbaryl were included in four of the previous studies. DDT was included in five of the previous studies, which is still less than 30% of the previous studies. This shows that the hazard ranking system used in the current study did identify pesticides as hazard priorities that would likely not have otherwise been chosen for analysis, underscoring the usefulness of applying the hazard ranking system prior to sampling.

Even specifically in Yuma County, the pesticides targeted in the current study were different than the three previous studies. The first study in Yuma County was a cohort of the National Human Exposure Assessment Study (NHEXAS) in 1995. That study included chlorpyrifos, diazinon, and malathion, which were known to be highly used organophosphates (OPs) during that time period in Yuma; most of these pesticides were detected, but at low levels near the analytical detection limit (Robertson et al., 1999). The next Yuma study, conducted by USEPA in 1996, also included chlorpyrifos, diazinon, and malathion, and it was specifically stated that the pesticides were chosen to match that of NHEXAS (O'Rourke et al., 2000). The USEPA study results were very similar to those of NHEXAS. In the third, and most recent sampling initiative, performed in 2000 by the Centers for Disease Control and Prevention (CDC), a large suite of pesticides was targeted that included organochlorines, organophosphates, carbamates, pyrethroids, and other pesticide families, but the rationale for the specific pesticides chosen was not specified (Thompson et al., 2005). In that study, the pesticides detected in at least 50% of the households sampled included permethrin (cis and trans isomers), chlorpyrifos, diazinon, propoxur, o-phenylphenol, and cypermethrin.

When the pesticides targeted in the current study were compared to those targeted in the CDC study, only the permethrin isomers and trifluralin were included in both studies. Bifenthrin, which was notably detected in all three media in the current study, was not included in any of the previous studies in Yuma County. Without implementation of the hazard ranking system, it is probable that bifenthrin would never have been chosen for the current study.

It is possible that the differences between the previous studies in Yuma County, Arizona compared to the current study are, at least partially, due to the 10-15 year time gap between those studies and the current one. The time range of the previous studies occurred during the transition period of dominant use of OPs in the agricultural industry to pyrethroids (Epstein and Bassein, 2003; USDA, 2006), and thus it was expected to still observe a heavy emphasis on OPs in sampling during that time period. These types of changes with time highlight why using the hazard ranking system prior to sampling can be so useful. Since recent agricultural pesticide application is one of the factors incorporated into the hazard ranking system, researchers are prevented from targeting pesticides that are no longer the main hazards, even if they had been in the past.

The measured levels of pesticides in the current study were also compared to those of the 19 prior studies. Among the previously described peer-reviewed studies that collected outdoor air samples at homes in an agricultural community, only Bradman et al. (2007) targeted any of the pesticides that were also included in the current study. The outdoor air levels of bifenthrin and permethrin reported by Bradman et al. (2007) are very similar to the current study. The maximum values for bifenthrin in Bradman et al. (2007) and in the current study were 2.9 ng/m^3 and 3.84

ng/m^3, respectively. The maximum value for permethrin in Bradman et al. (2007) was 8.0 ng/m^3 compared to 2.9 ng/m^3 in the current study.

There were no other peer-reviewed studies that reported outdoor air pesticide levels at homes in an agricultural community for any of the same pesticides of interest selected in the current study. However, there were alternative studies (i.e. not homes in an agricultural community) that sampled outdoor air for agricultural pesticides, and the results of those studies were similar to the current study. For example, one study in an agricultural community in the San Joaquin Valley of California monitored pesticides in the ambient air at three elementary schools over a period of one year (Wofford et al., 2015). In that study, the annual mean of trifluralin in the air was 3.64 ng/m^3 and the maximum trifluralin level measured during a 14-day period was 11.15 ng/m^3 (ibid). These results are very comparable to the current study's measured values for trifluralin, in which the mean value was 0.4 ng/m^3 and the maximum value was 12.2 ng/m^3. Permethrin was also targeted in Wofford et al., (2015), and it was reported that the annual mean of permethrin was 4 ng/m^3 and the maximum permethrin level measured during a 14-day period was 7 ng/m^3 (ibid). These levels are also similar to the sum of the cis and trans isomers of permethrin in the current study, where the mean value was non-detectable and the maximum level was 2.39 ng/m^3.

Next, airborne trifluralin levels were measured in a cotton field in New Mexico before and after mechanized soil management events in which trifluralin was applied to the soil using a tractor (Holmén et al., 2013). The mean daytime level of trifluralin prior to application was 25.66 ng/m^3, and this increased to a mean level of

48.46 ng/m^3 for a distance of up to 100 meters away from the tractor (ibid). These levels are higher than the maximum levels reported in the current study; however, this was expected since Holmén et al. (2013) sampled within the confines of an agricultural field, while the samples in the current study were taken at farmworker homes in an agricultural community.

Finally, in an older study that measured airborne pesticides along the Mississippi River, the trifluralin levels were comparable to, but a bit higher than, the measured values of the current study (Majewski et al., 1990). Specifically, the median trifluralin value in that study was 2.49 ng/m^3 (compared to 0.40 ng/m^3 measured in the current study) and the maximum trifluralin value was 80 ng/m^3 (compared to 12.2 ng/m^3 measured in the current study). The authors of that study also reported non-detectable values for carbaryl and pronamide, and cis-permethrin; this is very similar to the results of the current study in which carbaryl and pronamide were not detected in any air samples, and cis-permethrin was only detected in one air sample.

None of the previously described peer-reviewed studies in the literature collected outdoor soil or targeted any of the same pesticides selected in the current study. However, several of studies that collected house dust samples did include pesticides that are the same as the current study, namely DDT, carbaryl, bifenthrin, and permethrin (McCauley et al., 2001, Thompson et al., 2005, Bradman et al., 2007; Harnly et al., 2009; Gunier et al., 2011, Quirós-Alcalá et al., 2011).

Overall, the levels of DDT and carbaryl in the current study were similar to, or lower than, other studies reported in the peer reviewed literature. In the current study, none of the samples collected had detectable levels of DDT and only one sample had a detectable level of carbaryl (29.02 ng/g). Previously, Thompson et al., (2005) reported a geometric mean value of 63.4 ng/g for DDT and 346.8 ng/g for carbaryl in household dust samples collected in Yuma County, Arizona in 2000. The differences between the results of Thompson et al., (2005) compared to the current study highlight the changes that have occurred in Yuma County, Arizona over the past 10-15 years. More recently, Gunier et al., (2011) reported a median value of 26 ng/g in house dust for carbaryl in California homes; this is close to the maximum value measured in the current study of 29.02 ng/g. Finally, McCauley et al., (2001), which reported only the detection frequency of pesticides in the house dust, found that DDT and carbaryl were both detected in only 4% of the total samples collected from Oregon farmworkers' homes, which are similar results to the current study.

For the most part, the measured house dust levels of bifenthrin and permethrin in the current study were similar to that of other studies in the peer-reviewed literature. In the current study, the median level measured was non-detectable for bifenthrin. Previously, Bradman et al. (2007) and Quirós-Alcalá et al. (2011) both also reported non-detectable median levels of bifenthrin in the house dust. Likewise, the median level measured for permethrin in the current study was 524.71 ng/g; which is comparable to Bradman et al. (2007) and Harnly et al. (2009), who respectively reported median permethrin levels of 380 ng/g, and 811 ng/g. On the other hand, permethrin in the current study was a quite a bit lower than the year 2000 sampling study in Yuma County, Arizona that reported a geometric mean of permethrin of 1,678 ng/g (Thompson et al., 2005), as well as a recent study in California that reported a median level of 1,520 ng/g (Quirós-Alcalá et al., 2011).

2.4.5 Limited Variation of Pesticides in Previous Studies

Upon aggregating the pesticides from the previous 19 sampling studies, it was found that were a total of only 89 pesticides targeted across the agricultural communities (Table 2-8). Given that thousands of pesticides are applied agriculturally throughout the United States each year (Sugeng et al., 2013), it appears that researchers have targeted a rather limited variation of pesticides. Of these 89 pesticides: 56 were targeted in one of the 19 sampling studies, 20 were targeted in two of the studies, one was targeted in three of the studies, and three were targeted in four of the studies. Nine pesticides were targeted in five or more of the studies. These nine pesticides included DCPA, DDE, and DDT (each included in five studies), atrazine (included in six studies), azinphosmethyl and phosmet (each included in seven studies), diazinon (included in nine studies), malathion (included in 10 studies), and chlorpyrifos (included in 12 studies).

This limited variation of pesticides selected across the previous studies begs the question as to whether researchers sometimes target pesticides based on actual relevance to the agricultural community of interest, or, if on the other hand researchers have tend to simply default to pesticides targeted in previous studies. Based on the literature search performed, it appears that a combination of these approaches may have played a role in choosing which pesticides to target in sampling studies. The majority of the previous studies did provide rationale for the pesticides targeted, such as high local agricultural application of those particular pesticides, and as would be expected, many of the targeted pesticides were detected in the media sampled for most of those previous studies. Yet, there is other evidence that researchers in the previous studies may have been defaulting to pesticides that are somewhat "behind the times." It was observed that pesticides that were targeted for the majority of studies were organophosphates (OPs) (e.g., chlorpyrifos, diazinon, malathion, and phosmet), but this is a counterintuitive finding because although in the 1980s, OPs were the most common class of insecticides used in the United States, in more recent years, much of the OP application has been replaced with pyrethroids (Epstein and Bassein, 2003; Feo et al., 2010). An example of this phenomenon can be seen in pesticide use trends in California from 1992-2000 where mostly OPs were used to treat almonds and stone fruit orchards up until 1994, but then OP applications began to decrease as other pesticides, including pyrethroids, began to increase (Epstein and Bassein, 2003).

The change from OPs to pyrethroids is largely due to the fact that pyrethroids are able to target a wide variety of pests at lower application rates, with lower mammalian toxicity, and lower environmental persistence compared to OPs (Pap et al., 1996). In addition, by 2000, the USEPA had discontinued residential registration for chlorpyrifos and diazinon, two commonly applied OPs. This spurred a notable increase of pyrethroids on the market for both residential and agricultural purposes (USEPA, 2011b). Nonetheless, OPs are still applied in agriculture and accounted for around 40% of all insecticides applied throughout the United States in 2004 (ibid). However, also in 2004, pyrethroids could be detected in 43% of samples for certain crops, namely lettuce and spinach, illustrating the rising popularity of pyrethroids (USDA, 2006).

Among the agricultural studies included in the literature search, Bradman et al. (2007) chose to target both OPs and pyrethroids in its sampling performed in 2002. Results of that study showed a higher number of pyrethroids detected compared to the number of OPs. The fact that most previous pesticide sampling initiatives focused heavily on OPs, while pyrethroids were given relatively less attention could indicate that strategies to determine the most up-to-date relevant pesticides for sampling studies were lacking. It should be noted that some OPs, such as chlorpyrifos and diazinon, though still used in agriculture, are no longer registered for use inside the home, so these pesticides could be useful to target for the purposes of determining in-home levels derived solely from agricultural sources. Nonetheless, this potential motivation may be irrelevant for other OPs, such as malathion and phosmet, since they are currently approved for both residential and agricultural use.

2.4.6 Inclusion of Indoor and Outdoor Sampling: A Unique Contribution

A unique contribution of the current study, compared to the previous studies, was the inclusion of sampling both indoors and outdoors. Among the 19 previous sampling studies that have collected environmental samples (i.e., soil, outdoor air, indoor air, vacuumed house dust, or surface wipes), only eight studies included sampling of both outdoor and indoor media. The majority of the previous studies sampled indoor house dust, with 14 studies including vacuumed house dust and two studies including surface wipes. Only three studies included soil sampling, and four studies included outdoor air sampling. Prior to the current study, only one study sampled outdoor soil and air, along with indoor house dust.

By including outdoor soil and air, along with indoor house dust in the current study, insight into the potential transport pathways of pesticides from outdoors to the indoors was gained. The moderate positive correlations for bifenthrin between outdoor soil and outdoor air, along with between outdoor soil and indoor dust suggest that airborne bifenthrin is primarily particle bound and may enter homes through air infiltration of resuspended soil particles driven by the wind. The fact that the correlation for bifenthrin between the outdoor media was statistically significant, but this was not true for its correlation between outdoor media and indoor media suggests that the relationships between outdoor and indoor media may be more complex than that of two types of outdoor media. It is plausible that there are other driving factors underlying the extent to which outdoor pesticides can enter into homes, and further assessment is needed to better understand risk factors for detection in homes. A similar moderate positive correlation between permethrin in outdoor soil and indoor dust was observed, but due to the low detection frequency in outdoor air, other correlations could not be performed, and thus it is difficult to make a valid assessment as to whether permethrin followed the same trend as bifenthrin. These correlations could also not be performed for trifluralin due to low detection frequency in both outdoor soil and indoor dust.

2.4.7 Conclusions

The current study's detection of multiple pesticides in yard soil, outdoor air, and house dust at farmworkers' homes suggest that agricultural pesticides are indeed transported away from agricultural fields and into homes. Use of the pesticide hazard ranking system prior to sampling the yard soil, outdoor air, and house dust at farmworkers' homes in Yuma County identified relevant pesticide hazard priorities. The limited variation of targeted pesticides in previous agricultural pesticide sampling studies, which were found to largely be different than the pesticides identified for analysis in the current study, suggests that researchers may at least partially be defaulting to pesticides that have been targeted in previous studies. This highlights the uniqueness of the pesticides targeted for the current study, and suggests that applying a hazard ranking system prior to pesticide analysis may optimize pesticide sampling.

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes

Citation	**Study Time Period and Location**	**Study Population**	**Pesticides Targeted (bold denotes inclusion in current study)**	**Rationale for Pesticides Targeted**	**Major Findings**	**Media Sampled**
Bradman et al., 1996	1992; San Joaquin Valley, California	Farmworker families versus non-farmworker families	Aldrin, atrazine, **carbaryl**, captan, trans-chlordane, chlorothalonil, chlorpyrifos, dacthal, DDE, **DDT**, diazinon, dichloran, dieldrin, **endosulfan**, heptachlor, heptachlor epoxide, lindane malathion, methidathion, methyl parathion, methoxychlor, naled, nonachlor, norflurazon, octachloronophthalene, oxychlordane, oxyfluorfen, phosmet, propoxur, runnel	Most highly used pesticides in area associated with health effects	Most commonly detected pesticides diazinon and chlorpyrifos in farmworker homes	Vacuumed floor dust
Simcox et al., 1995	1992; Wenatchee area in eastern Washington state	Farmworker families versus non-farmworker families	Aziphosmethyl, chlorpyrifos, ethyl parathion, phosmet (all OPs)	Highly used OPs in area	Higher detection in homes of farmworker families; azinphosmethyl most commonly detected in farmworker families	Vacuumed floor dust, soil

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	**Study Time Period and Location**	**Study Population**	**Pesticides Targeted (bold denotes inclusion in current study)**	**Rationale for Pesticides Targeted**	**Major Findings**	**Media Sampled**
Robertson et al., 1999	1995; Yuma County, Arizona	Families with children in agricultural community (NHEXAS-AZ cohort)	Chlorpyrifos, diazinon, malathion	Highly used OPs in area	Detected, but at low levels near analytical detection limit	Indoor air, outdoor air, outdoor soil, vacuumed floor dust
Lu et al., 2000	1995; Wenatchee area in eastern Washington state	Pesticide applicator families versus farmworker families versus non-farmworker families	Aziphosmethyl, chlorpyrifos, ethyl parathion, phosmet (all OPs)	Highly used OPs in area	Pesticides in house dust: applicator families>farmworker families>non-farmworker families Low detection frequencies overall; azinphosmethyl and Phosmet in house dust decreased from sampling in 1992	Floor wipes, vacuumed floor dust, vehicle wipes
O'Rourke et al., 2000	1996; Yuma County, Arizona	Families with children in agricultural community	Chlorpyrifos, diazinon, malathion	Highly used OPs in area (matching NHEXAS)	Similar results as NHEXAS Arizona; exception was chlorpyrifos found in outdoor air	Indoor air, outdoor air, vacuumed floor dust

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	**Study Time Period and Location**	**Study Population**	**Pesticides Targeted (bold denotes inclusion in current study)**	**Rationale for Pesticides Targeted**	**Major Findings**	**Media Sampled**
McCauley et al., 2001	1997; Northwest Oregon	Migrant farmworker homes	Azinphosmethyl, captan, **carbaryl**, **DDT**, DDE, dursban, malathion, pentachlorphenol, phosmet, piperolyl butoxide	Previously found those pesticides in local homes	High detection frequency of azinphosmethyl and captan	Vacuumed floor dust
Ward et al., 2006	1998; Iowa	From case-control study of non-Hodgkin lymphoma in agricultural community	2,4-D, acetochlor, alachlor, atrazine, bentazon, bromoxynil, cyanazine dicamba, fenoxyprop ethyl, fluazifop-p-butyl, metolachlor, metribuzin, pendimethalin	Highly used pesticides in area from 1985-1995	Agricultural pesticides in 28% of homes; highest in homes with active farmer; increased in home by acreage of nearby field	Vacuumed floor dust
Harnly et al., 2009	1999; Salinas Valley, California	Homes of agricultural families (CHAMACOS cohort)	Acephate, azinphosmethyl, bensulide, chlorpyrifos, dacthal, DCPA, DDE, **DDT**, diazinon, dimethoate, fenamiphos, fonofos, iprodione, malathion, methamidiphos, methidathion, methomyl, oxydemeton-methyl, phosmet, **permethrin**, vinclonzoline	Highly used pesticides in area; analytical capability; chemical characteristics	All analytes present in all dust samples; acephate and azinphosmethyl had highest levels	Vacuumed floor dust

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	Study Time Period and Location	Study Population	Pesticides Targeted (bold denotes inclusion in current study)	Rationale for Pesticides Targeted	Major Findings	Media Sampled
Thompson et al., 2003	1999; Yakima Valley, Washington State	Farmworker homes with children	Azinphosmethyl, chlorpyrifos, diazinon, malathion, methyl-parathion, phosmet (all OPs)	Highly used OPs in area	All OPs detected, azinphosmethyl highest detection frequency	Vacuumed floor dust, vacuumed vehicle dust
Thompson et al., 2005	1999; Yuma, Arizona	Families in agricultural community	Atrazine, azinphosmethyl, bendiocarb, bensulide, benzamide captan, **carbaryl**, carbofuran, chlordane, chlorpyrifos, cypermethrin, DCPA, DDD, DDE, **DDT**, diazinon, dichlorvas, dicofol, dieldrin, disulfoton, **endosulfan**, ethyl, folpet, fonofos, gamma-chlordane, heptachlor, lindane, malathion, methyl parathion, methoxychlor, parathion, **permethrin**, pendimethalin, phenylphenol, phorate, property, propoxur, simazine, terbufos, **trifluralin**	Rationale not specified	Azinphosmethyl, chlorpyrifos, and ethyl parathion had highest detection frequencies (21-25%)	Vacuumed floor dust

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	Study Time Period and Location	Study Population	Pesticides Targeted (bold denotes inclusion in current study)	Rationale for Pesticides Targeted	Major Findings	Media Sampled
Shalat et al., 2003	2000; South Texas	Families in agricultural community	Azinphosmethyl, chlorpyrifos, demoton-o, demoton-s, diazinon, disulfoton, ethion, fenithrothion, fonofos, malathion, ethyl/methyl parathion (all OPs)	Highly used OPs in area	OPs detected in 76% of homes	Floor wipe, soil
Curwin et al., 2005	2001; Keokuk and Mahaska counties, Iowa	Farmworker homes versus non-farmworker homes	2,4-D, acetochlor, alachlor, atrazine, glyphosate, metolachlor, chlorpyrifos	Highly used pesticides in area	Pesticides detected in farmworker and non-farmworker homes but higher in farmworker homes	Indoor air, outdoor air, surface wipes, vacuumed floor dust
Weppner et al., 2006	2001, Central Washington State	Families living in agricultural community with children	Methamidophos	Nearby fields sprayed with methamidophos-hos	Deposition in community lower compared to in fields; residues outside post-applications, but not indoors	Indoor air, outdoor air, surface wipes
Gunier et al., 2011	2001 and 2006; Northern and central California	Homes in agricultural community (from Northern California Childhood Leukemia Study)	**Carbaryl**, chlorpyrifos, chlorthal-dimethyl, diazinon, iprodione, phosmet, simazine	Previously detected in study population; highly used pesticides in area	High detection of all pesticides (34-96%)	Vacuumed floor dust

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	Study Time Period and Location	Study Population	Pesticides Targeted (bold denotes inclusion in current study)	Rationale for Pesticides Targeted	Major Findings	Media Sampled
Bradman et al., 2007	2002; Salinas Valley, Monterey County, California	Homes of children with at least one farmworker	Acephate, **bifenthrin**, chlorthal-dimethyl, cis-allethrin, chlorpyrifos, DDE, **DDT**, gamma-cyhalothrin, cyfluthrin, cypermethrin, deltamethrin, diazinon, dichlorvos, dimethoate, esfenvalerate, fonofos, iprodione, malathion, **permethrin**, resmethrin, sumithrin, trans-allethrin	Highly used pesticides in area, likelihood of home pesticide use, and analytical capability	A higher number of pyrethroids detected compared to the number of OP pesticides	Vacuumed floor dust, indoor air, outdoor air, surface wipes and presses
Golla et al., 2012	2005; Cedar and Johnson counties, Iowa	Families living on a farm	Atrazine	Known to be applied to farmland	Atrazine in homes during the planting season	Vacuumed floor dust
Quirós-Alcalá et al., 2011	2006; Salinas, California	Farmworker homes	Allethrin, **bifenthrin**, chlorpyrifos, chlorthal-dimethyl, cypermethrin, deltamethrin, diazinon, diazinon-oxon, esfenvalerate, imiprothrin, iprodione, malathion, methidathion, methyl parathion, **permethrin**, phorate, piperonyl butoxide, prallethrin, sumithrin, tetrachlorvinphos	Highly used pesticides in area, Previously detected in study population; analytical capability	Most analytes measured; majority of homes had at least three analytes detected; chlorpyrifos and diazinon most commonly detected	Vacuumed floor dust

Table 2-8: Agricultural Pesticide Sampling of Environmental Media at Homes (continued)

Citation	**Study Time Period and Location**	**Study Population**	**Pesticides Targeted (bold denotes inclusion in current study)**	**Rationale for Pesticides Targeted**	**Major Findings**	**Media Sampled**
Lozier et al., 2012	2007; Eastern Iowa	Homes of commercial applicators	Atrazine	Highly used pesticides in area, toxicity, previously detected in area	Atrazine detection corresponded to handling at work	Vacuumed floor dust
Armstrong, 2013	2011; Yakima Valley, Washington	Farmworker and non-farmworker families in agricultural community	Azinphosmethyl, azinphosmethyl-oxon, chlorpyrifos, chlorpyrifos-oxon	Highly used pesticides in area	Detection frequency much higher outside than inside	Indoor air, outdoor air

CHAPTER 3

MODELING THE RELATIVE CONTRIBUTIONS OF THE AIR INFILTRATION AND SOIL TRACK-IN PATHWAYS OF AGRICULTURAL PESTICIDES INTO THE HOUSE DUST AND THE RESIDENCE TIMES OF AGRICULTURAL PESTICIDES IN THE HOUSE DUST

3.1 Introduction

3.1.1 Previously Developed Soil Contaminant Transport Model

This current study utilized and modified a soil contaminant transport model previously developed by Layton and Beamer (2009) to estimate the relative contributions of the soil track-in and air infiltration pathways of inorganic contaminants into the house dust, along with the residence time of particles in the house dust. This model was based on a series of mass-balance equations designed to capture the transport of contaminated soil and airborne particles into a home, along with the subsequent indoor distribution due to resuspension and deposition processes. The model accounts for house dust formation as a mixture of particulate matter from air infiltration, soil tracked-in on shoes, clothes, and skin, and organic matter from sources such as organic fibers and skin cells. Resuspension and deposition processes between the indoor air compartment and the floor compartment, along with removal through building exfiltration of suspended particles and cleaning practices are also expressed through the series of equations. A complete portrayal of transport processes for the soil contaminant transport model can be viewed in Figure 3-1 (Layton and Beamer, 2009).

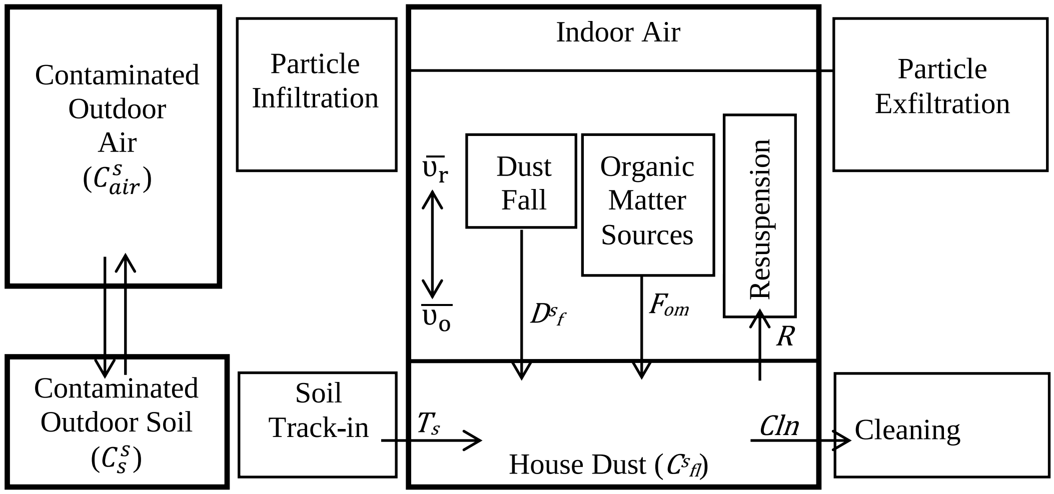


Figure 3-1: Conceptual Diagram of Soil Contaminant Transport Model, Depicting Movement of Contaminated Soil and Airborne Particles in and out of a Home, Along With Indoor Distribution Processes (Layton and Beamer, 2009)

This mass-balance model uses a set of differential equations to capture the time-varying mass-balance relationships, which can also be solved as steady-state solutions in which it is assumed that the input is equal to the output and no accumulation occurs. Full differential equations and limited steady-state solutions can be viewed in the Supplemental Information of Layton and Beamer (2009).

A series of formulas were derived to estimate the following transport parameters: track-in rate of soil (T_s), deposition velocity of outdoor-derived particulate matter ($\overline{\upsilon_o}$), deposition velocity of resuspended particulate matter onto floor surfaces ($\overline{\upsilon}_r$), resuspension rate of floor particles into indoor air (R), flux of organic matter onto floor surfaces (F_{om}), and a first-order particle removal rate from floors due to cleaning (Cln). Estimating the transport parameters required multiple inputs, which were determined by Layton and Beamer (2009) through a variety of sources and methods. The model developers used residential monitoring data for arsenic from the National Human Exposure Assessment Survey (NHEXAS) performed in USEPA Region 5, which are the Midwestern states, along with data on lead contamination in homes located in Sacramento, California and Arnhem, Netherlands. A fixed ceiling height of 2.4 meters was calculating by dividing the volume for detached single-family homes in the United States, 312 m^3, based on the geometric mean reported in Murray and Burmaster (1995) by the median area for occupied, detached and mobile homes, 167 m^2, as reported in the American Housing Survey for the United States: 2005 (US Department of Housing and Urban Development, 2006). The air exchange rate, 8.6 $d\text{-}^1$, was based on the geometric mean reported in Murray and Burmaster (1995) for Midwestern states. The unitless penetration factor was assumed to be one, representing completely effective penetration. This assumption was based on the logic that the majority of the homes in the cities of interest did not use energy-efficient building techniques, and therefore, there was no reason to believe there would be reduced building penetration. The organic matter content of soils and outdoor aerosols were calculated based on literature values reported for organic carbon across 46 cities in the United States (Shah et al., 1986). The final estimated value for each transport parameter value can be viewed in Table 3-1. Please see the Supplemental Information of Layton and Beamer (2009) for the full equations used to derive each transport parameter.

Table 3-1: Estimated Values of Transport Parameters for the Soil Contaminant Transport Model (Layton and Beamer, 2009)

Transport Parameter	**Parameter Explanation**	**Estimated Value**
Cln	First-order particle removal rate from floor due to cleaning (d^{-1})	0.0053
F_{om}	Flux of organic matter onto floor surface (d^{-1})	0.074
R	Resuspension rate of floor particles into indoor air (d^{-1})	0.011
T_s	Rate of soil track-in to home (d^{-1})	0.099
$\overline{\upsilon_o}$	Mean deposition velocity of outdoor-derived particulate matter settling onto floor surfaces ($m \cdot d^{-1}$)	18.6
$\overline{\upsilon_r}$	Mean deposition velocity of resuspended particulate matter onto floor surfaces ($m \cdot d^{-1}$).	175.0

3.1.2 Soil Contaminant Transport Model Evaluation and Application

The previously developed soil contaminant transport model was subsequently evaluated by one of the model developers, Dr. Beamer, by using data from homes in a southern Arizona community living near a hazardous waste site with high levels of metals/metalloids, known as the Saginaw Hill (SH) Study (Beamer et al., 2009a). Concentrations of arsenic and lead in floor dust were estimated using Equation 3-1, which assumes a steady-state. For reference, the differential form of Equation 3-1 can be seen in Equation 3-2. Table 3-2 describes each of the input variables that were used to estimate the metal concentrations in the floor dust and how each input variable was obtained.

$$Equation\ 3-1:\ \ C_{fl}^{s} = \frac{(C_{om}^{s} \cdot F_{om} + C_{s}^{s} \cdot T_s + D_f^s \cdot A_{fl})}{M_{fl} \cdot A_{fl}(R + Cln)}$$

$$Equation\ 3-2:$$
$$\frac{d\left(C_{fl}^{s}\right)}{dt} = \frac{(C_s^s \cdot\ T_s + C_{om}^s \cdot F_{om} + D_f^s \cdot A_{fl} - C_{fl}^s \cdot M_{fl} \cdot A_{fl}(R + Cln)}{(M_{fl} \cdot A_{fl})}$$

Table 3-2: Measured Input Variables for Each Home to Estimate the Concentration of the Substance in Floor Dust (C^{s}_{fl}) in SH Study

Variable	**Variable Explanation**	**Method to Obtain**
A_{fl}	Floor area (m^2)	Measured in SH study
C_{om}^s	Concentration of inorganic substance in indoor organic matter (μg/g)	Assumed to be 0 from Layton and Beamer (2009)
C_s^s	Concentration of inorganic substance in outdoor soil (μg/g)	Measured as part of SH study
D_f^s	Deposition rate of inorganic substance ($\mu g \cdot m^2/d$)	Measured as part of SH study
M_{fl}	Mass loading of particles onto floor surface ($g \cdot m^2$)	Measured as part of SH study
Cln, F_{om}, R, T_s	Transport parameters described in Table 7-1	Referenced from Layton and Beamer (2009)

Using a Wilcoxon rank sum test, with an alpha level of 0.05, it was determined that there was no significant difference between the estimated and measured house dust concentrations for arsenic and lead; as such, the model was successfully evaluated.

The relative contribution of arsenic and lead into the house dust via air infiltration (IN_{air}^{s}) and soil track-in (IN_{soil}^{s}) in the SH study were estimated using Equation 3-3 and Equation 3-4, respectively. For this application of the model, the air exchange rate (Ach) was assumed to be 11.52 d^{-1}, an empirically derived 50^{th} percentile for the Southwest region for the months of January, February and March (Murray and Burmaster, 1995). The dimensionless penetration factor representing particle removal efficiency of building shell (P) was assumed to be one. The mean deposition velocity of outdoor-derived particulate matter settling onto floor surfaces

($\overline{\upsilon_o}$) was estimated using Equation 3-5 which incorporated the dust fall rate (D_f^s), concentration of the inorganic substance in dust fall (C_{df}^s), concentration of the inorganic substance in the floor dust (C_{fl}^s), and concentration of the inorganic substance in total suspended particles indoors ($C_{tsp\_in}^s$). Relevant transport parameters from Table 7-1 were also used. Residence time (τ_{fl}^s), which is the amount of time the substance persists in particles in the floor dust, was estimated using Equation 3-6.

$$Equation\ 3-3:\quad IN_{air}^s = \frac{Ach \cdot P \cdot H \cdot C_{air}^s}{\overline{\upsilon_o} \cdot Ach \cdot H}(\overline{\upsilon_o} \cdot A_{fl})$$

$$Equation\ 3-4:\quad IN_{track}^s = C_s^s \cdot T_s$$

$$Equation\ 3-5:\quad \overline{\upsilon_o} = \frac{D_f^s\left(C_{df}^s - C_{fl}^s\right)}{TSP_{in}(C_{fl}^s - C_{tsp\_in}^s)}$$

$$Equation\ 3-6:\quad \tau_{fl}^s = (R + Cln)^{-1}$$

The results of the SH study model application showed that the air infiltration pathway contributed to more than 85% of the arsenic and lead measured in house dust, despite the fact that ambient air levels were low for both arsenic and lead (<1 ng/m^3) compared to levels in the soil (5-10 mg/kg) (Beamer et al., 2009a). This suggests that air infiltration is the main transport pathway of inorganic contaminants into the house dust. The results also showed that the residence time of floor particles was 61 days (Beamer et al., 2009a), which suggests that detection of the inorganic contaminants over a long period of time be a result of continued transport into the home.

3.1.3 Major Aim and Hypotheses

Since the original soil contaminant transport model was developed for use with inorganic contaminants, such as arsenic and lead, it was unclear whether the relative contributions of the soil track-in and air infiltration pathways into the home, along with the residence times, would be similar for agricultural pesticides. There are two major differences between inorganic contaminants and pesticides that could affect transport in the environment. First, inorganic contaminants are transported via suspended particulate matter in the air (Layton and Beamer, 2009), while the semi-volatile nature of pesticides results in partitioning between the particle and vapor phase (ATSDR, 2003, Harner and Bidleman, 1998). Second, inorganic contaminants are resistant to decay in the environment (Chung et al., 2014), while pesticides are known to decay over time (ATSDR, 2003).

The first major aim of this dissertation was to estimate the relative contributions of the air infiltration and soil track-in pathways into the house dust of farmworkers' homes, and to also estimate the residence time of the agricultural pesticides in house dust by developing, evaluating, and applying a pesticide transport model. It was hypothesized that air infiltration is the dominant pathway of agricultural pesticides into the farmworkers' house dust, which could shed light on why the Para Niños Saludables intervention (Thompson et al., 2008; Strong et al., 2009), previously described in Chapter 1, was not successful at reducing pesticide levels in the house dust after targeting behaviors related to the take-home/soil track-in pathway. It was also hypothesized that the residence time of pesticides in the house dust is less than one year, which would suggest that residence time was not the underlying reason why the Para Niños Saludables intervention was unsuccessful given that the time between baseline and follow-up testing in that intervention was four years.

3.2 Methods

3.2.1 Modifying the Soil Contaminant Transport Model to Develop a Pesticide Transport Model

In order to be applicable for use in developing a pesticide transport mode, the soil contaminant transport model needed to be modified to account for the differences between inorganic contaminants and pesticides, described previously. This necessitated that the pesticide transport model incorporate processes relevant to pesticides (Figure 3-2). As such, chemical decay (*k)* was included in the removal processes. In addition, the deposition rate of the pesticide into the house dust ($D^{p}_{f\_part}$) took into account particle-vapor partitioning in the air, and it assumed only the portion of the pesticide that adheres to particles contributed to deposition into the house dust via dust fall.

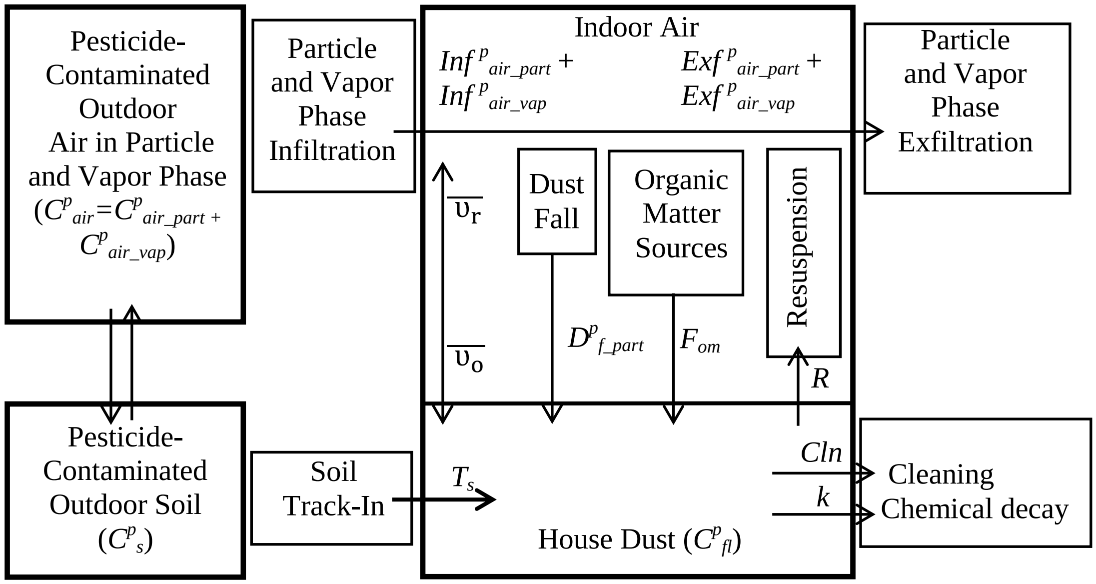


Figure 3-2: Conceptual Diagram of Pesticide Transport Model, Adapted from Soil Contaminant Transport Model (Layton and Beamer, 2009) with Modifications to Account for Particle-Vapor Partitioning and Chemical Decay of Pesticides

3.2.2 Estimating Particle-Vapor Partitioning of Outdoor Air Samples

The outdoor air samples, collected with a low-volume polyurethane foam (PUF) cartridge packed with XAD-2 resin, were analyzed for pesticides as a bulk sample, which did not separate particle and vapor phases. In order to estimate the phase distribution for each pesticide of interest, partitioning between the two phases was determined using the K_{OA} Absorption Model, which uses the octanol-air partition (K_{OA}) to describe the absorption of a compound to airborne particles (Harner and Bidleman, 1998). The K_{OA} Absorption Model assumes that gaseous compounds can absorb to the organic matter of airborne particles. This Model was chosen for use in the current study based on the findings of Harner and Bidleman (1998). In that study, experimental data of various semi-volatile compounds in air samples were compared with the estimates of multiple particle-vapor partitioning models, and the authors determined that the K_{OA} Absorption Model was simpler than the alternative models and fit the experimental data the best. As such, the following equations, based on the K_{OA} Absorption Model (Harner and Bidleman, 1998), were used to solve for the fraction on particles (Φ) (Equation 3- 7) and in the gas phase (γ) (Equation 3-8).

$$Equation\ 3-7:\ \ \Phi = \frac{K_P \cdot TSP}{1 + K_P \cdot TSP}$$

$$Equation\ 3-8:\ \ \gamma = 100 - \Phi$$

The mean total suspended particles (TSP) was referenced from the SH study, where it was measured for each home. The particle/vapor coefficient (K_P) was calculated using Equation 3-9 (Harner and Bidleman, 1998).

$$Equation\ 3-9:\ \ K_P = 10^{(logK_{OA}+logf_{om}-11.91)}$$

In order to solve for K_P, the fraction of organic matter in particulate matter (f_{om}) and the octanol-air partition coefficient (K_{OA}) were needed. A peer-reviewed literature search to find the most reasonable value for f_{om} uncovered that the fraction of organic carbon (f_{oc}) is more commonly reported rather than the fraction of organic matter (f_{om}). Based on the finding that the average organic carbon in aerosol samples across 46 urban sites and 20 rural sites in the United States was approximately 8% (Shah, 1986), and the well-accepted conversion from fraction of organic carbon (f_{oC}) to fraction of organic matter (f_{om}) of $f_{oc} \approx 0.58\ f_{om}$ (Weiner, 2013), f_{om} was estimated to be 14%. Further justification for using 14% for the f_{om} value, as calculated from the average f_{oc} in Shah (1986), is based on the comparison of the average organic matter in a typical soil to the average organic matter in the current study's soil. It is known that typical soil is comprised of approximately 5% organic matter (Saljnikov, 2013), and the soil of the current study was also measured to be 5%. Therefore, it is reasonable to believe that f_{om} for particulate matter in this study should also be near the average value of f_{om} for particulate matter.

K_{OA}, the octanol-air partition coefficient, was estimated (Equation 3-10) based on the pesticide's octanol-water partition coefficient (K_{OW}) and Henry's Constant (H), along with the average temperature across all sampling periods (T) and the ideal gas constant (R), which is 8.314 Pa·m^3/K·mol. The equation used to estimate K_{OA} in the current study (Equation 3-10) has been widely used in the peer-reviewed literature to estimate the K_{OA} of organic chemicals, including pesticides (Paterson et al., 1991; Sadiki and Poissant, 2008; Qiu et al., 2008; Yu et al., 2012).

$$Equation\ 3-10:\ \ K_{OA} = K_{OW} \cdot \frac{R \cdot T}{H}$$

3.2.3 *Estimating Pesticide Decay Rate (k) and Indoor Half-life* ($t_{1/2}$)

The pesticide decay rate (k) was assumed to follow the first-order reaction rate, which can be justified by previous experimental findings that the degradation rate of both bifenthrin and permethrin are appropriately described by the first-order kinetic model (Baskaran et al., 1999; Lee et al., 2003; Liu et al., 2005). The first-order reaction rate is a linear model that assumes the reaction rate is directly proportional to the concentration of the reactant. The following describes the integration of the first-order differential rate law assuming the general differential rate law to be: $r = -\frac{D[C]}{[C]}$ and the 1st-order reaction rate equation to be: $r = -k[C]$.

$$r = -\frac{d[C]}{[C]} = -k[C] \rightarrow \int_{[Co]}^{[Cf]} \frac{1}{[C]} d[C] = -kdt = -\int_{[to]}^{[tf]} kdt$$

$\ln(Cf) - \ln(Co) = -k(tf - to)$

- Based on integration rule: $\int \frac{1}{x} dx = \ln(x) + C$

$\ln(Cf) = -kt + \ln(Co)$ (y=mx+b form, where –k is the slope)

$\ln(Cf) - \ln(Co) = -k(tf - to) \rightarrow \ln\left(\frac{Cf}{Co}\right) = -kt \rightarrow \ln(Cf) = -kt + \ln(Co)$

- Based on log rule: log $log_b\left(\frac{m}{n}\right) = log_b(m) - log_b(n)$

$e^{\ln(Cf)} = e^{\ln(Co)-kt}$

$Cf = Co \cdot e^{-kt}$ (final integrated first order decay rate equation)

The final integrated first-order decay rate equation was re-arranged to solve for the decay rate constant (k). The time (t) used was the estimated half-life of the pesticide in indoor dust ($t_{1/2}$). The following algebra was used to compute k:

$$(Cf) = \frac{1}{2}(Co)$$

$$\frac{(Cf)}{(Co)} = \frac{1}{2} = e^{-kt_{1/2}}$$

$$\ln\left(\frac{1}{2}\right) = -kt_{1/2}$$

$$\ln(1) - \ln(2) = -kt_{1/2}$$

$$\frac{\ln(2)}{t_{1/2}} = k$$

Therefore, the final equation to solve for k is expressed in Equation 3-11 as follows:

$$Equation\ 3-11{:}\ \ k = \frac{\ln(2)}{t_{1/2}}$$

Although soil half-life values of pesticides are widely documented, it is known that chemical break-down may be limited indoors due to the lack of outdoor degradation processes, such as wind erosion and photolysis (Wilford et al., 2005; Rudel and Perovich, 2009). It was, therefore, necessary to determine whether the half-life in indoor dust could reasonably be considered the same as the outdoor soil for bifenthrin and permethrin.

One previous study, which reported the soil half-life of permethrin to be 28 days, also reported that when permethrin was applied a thin film on plywood indoors near a window, 60% of the applied chemical remained after 20 days (IPCS, 1990). The author of this dissertation used interpolation to determine the number of days until 50% of the applied chemical remained. A line was plotted to describe the percent of degradation of the compound along the x-axis and the time point (days) along the y-axis. The only two known two points were (0, 1) and (0.4, 20), so a third point, (0.7, 40) was added, assuming that a consistent degradation pattern continued. Next, the linear trend-line equation was fitted to the plot and the R^2 of the trend-line was reported (R^2=0.9906). The resultant fitted trend-line equation was y=55.27x+0.0676. It was found that 50% of degradation indoors occurred at 28 days, which was the same as the reported outdoor soil half-life.

Also, permethrin was reported to be 10-100 times more photostable than synthetic pyrethroids developed in earlier years (Elliott et al., 1973), further suggesting that the outdoor degradation would not be much greater than the indoor degradation rate. Based on the assumption that pesticides were developed to be more photostable with time, and the fact that bifenthrin was developed a few years after permethrin (Palmquist et al., 2012), it is reasonable to believe that bifenthrin is at least as photostable as permethrin. As such, it was assumed that the soil half-life of bifenthrin could be reasonably used as the indoor dust half-life for bifenthrin.

3.2.4 Updated Equations for Pesticide Transport Model

Pesticide concentrations in the floor dust (C_{fl}^{p}) were used for evaluation of the pesticide transport model by determining whether there was a significant difference between the measured and estimated C_{fl}^{p} values. Derivation of the formula for C_{fl}^{p} at steady-state (Equation 3-12) was based on the formula for C_{fl}^{s} at steady-state

(Equation 3-1) in the original soil contaminant transport model. However, C_{fl}^{p} incorporates the modifications described earlier for pesticides.

$$Equation\ 3-12{:}\quad C_{fl}^{p} = \frac{(C_{om}^{p} \cdot F_{om} + C_{s}^{p} \cdot T_{s} + D_{f\_part}^{p} \cdot A_{fl})}{M_{fl} \cdot A_{fl}(R + Cln + k)}$$

All of the variables in Equation 3-12 were measured, calculated, referenced from the results of the (SH) study (Beamer et al., 2009a) or referenced from the derived transport parameters by the original model developers (Layton and Beamer, 2009). The deposition rate of pesticides ($D_{f\_part}^{p}$), one of the input variables for Equation 3-12, was not measured in the current study, and therefore, this variable was calculated using Equation 3-13.

$$Equation\ 3-13{:}\quad D_{f\_part}^{p} = \left(\overline{\upsilon_{o}} \cdot C_{in\_o}^{p}\right) + (\overline{\upsilon_{r}} \cdot C_{in\_r}^{p})$$

$C_{in\_o}^{p}$ is the concentration of pesticides in indoor air derived from infiltration of outdoor air (μg/m^3) and $C_{in\_r}^{p}$ is the pesticide concentration in indoor air due to resuspension processes (μg/m^3). It was necessary to calculate both $C_{in_o}^{p}$and $C_{in\_r}^{p}$ as well, which are expressed as Equation 3-14 and Equation 3-15, respectively. A list of all of the input variables, and how they were obtained, can be seen in Table 3-3.

$$Equation\ 3-14{:}\quad C_{in\_o}^{p} = \frac{Ach \cdot C_{tspo}^{p} \cdot P \cdot V}{Ach \cdot V + k \cdot V + A_{fl} \cdot \overline{\upsilon_{o}}}$$

$$Equation\ 3-15:\ \ C_{in\_r}^{p} = \frac{Ach \cdot C_{fl}^{p} \cdot M_{fl} \cdot V}{Ach \cdot V + k \cdot V + A_{fl} \cdot \overline{\upsilon_o}}$$

C_{fl}^{p} was estimated using Equation 3-16, which incorporates the substitutions for $D_{f\_part}^{p}$.

$$Equation\ 3-16: C_{fl}^{p} =$$

$$\frac{(C_{om}^{p} \cdot F_{om} + C_{s}^{p} \cdot T_s + \left(\overline{\upsilon_o} \cdot C_{in\_o}^{p} + \overline{\upsilon_r} \cdot C_{in\_r}^{p}\right) \cdot A_{fl} - C_{fl}^{p} \cdot M_{fl} \cdot A_{fl}(R + Cln + k))}{M_{fl} \cdot A_{fl}}$$

Table 3-3: Input Variable to Estimate C_{fl}^{p} in Pesticide Transport Model

Variable	Variable Explanation	Method to Obtain
Ach	Air exchange rate (d^{-1})	Referenced percentile distributions (Pandian et al., 1998)
A_{fl}	Floor area (m^2)	Measured for each home
Cln	First-order removal rate from floors due to cleaning (d^{-1})	Assumed to be 0.0053 (Layton and Beamer, 2009)
C_{om}^{p}	Concentration of pesticide in indoor organic matter (μg/g)	Assumed to be 0 (Layton and Beamer, 2009)
C_{s}^{p}	Concentration of pesticide in outdoor soil (μg/g)	Measured for each home
C_{tspo}^{p}	Bulk concentration of pesticide in suspended outdoor air particles (μg/g)	Calculated: $C_{tspo}^{p} = \frac{\Phi \cdot C_{air}^{p}}{TSP_o}$ Φ: calculated fraction on particles (Equation 3-7) C_{air}^{p}: measured outdoor air concentration TSP_o: referenced from SH study
$D_{f\_part}^{p}$	Deposition rate of pesticide adhered to particles ($\mu g \cdot m^2/d$)	Calculated for each home (Equation 3-13)
F_{om}	Flux of organic matter onto floor surface (g/d)	Assumed to be 0.074 (Layton and Beamer, 2009)
k	First-order pesticide decay rate (d^{-1})	k calculated (Equation 3-11) using range of soil half-lives referenced from peer-reviewed literature
M_{fl}	Mass loading of pesticides on particles onto floor surface (g/m^2)	Measured for each home
P	Penetration factor representing removal efficiency of pesticides on particles	Assumed to be 0.95-1.0 (Layton and Beamer, 2009)
R	Resuspension rate of pesticides adhered to floor particles into indoor air (d^{-1})	Assumed to be 0.011 (Layton and Beamer, 2009)
T_s	Soil track-in rate to house (g/d)	Assumed to be 0.099 (Layton and Beamer, 2009)
TSP_o	Total suspended particles outdoors (g/m^3)	Assumed to be 20.9 as mean value from SH study (unpublished)
V	Indoor air volume (m^3)	Calculated using $A_{fl} \cdot H$
$\overline{\upsilon_o}$	Deposition velocity of outdoor-derived pesticides adhered to particles settling onto floor (m/d)	Assumed to be 14-26 (Thatcher and Layton, 1995)
$\overline{\upsilon_r}$	Deposition velocity of resuspended pesticides adhered to particles onto floor (m/d)	Assumed to be 135-234 (Thatcher and Layton, 1995)

3.2.5 Stochastic Model Evaluation

3.2.5.1 Overview

The general method of model evaluation consisted of comparing the stochastically estimated bifenthrin C_{fl}^{p}values to the measured bifenthrin C_{fl}^{p}values. Bifenthrin was used for the model evaluation because the detection frequency in soil, dust, and air were all reasonably high (>35%). Permethrin, on the other hand, had only a detection frequency of 19% in the outdoor air, and thus, permethrin was determined to be unfit to be used for the model evaluation. A Monte Carlo simulation approach, which uses repeated random sampling (Driels and Shin, 2004; Raychaudhuri, 2008), was used to generate distributions of input variables to stochastically estimate C_{fl}^{p}, the relative contributions of air infiltration (IN_{air}) and soil track-in (IN_{track}), and the residence time of pesticides in the floor dust (τ_{fl}^{p}). All steps for the model evaluation were performed in RStudio Version 0.98.1103 (R Core Team, 2015).

3.2.5.2 Distribution Fitting of Input Variables

A process of distribution fitting was performed for each of the input variables needed to estimate C_{fl}^{p}. Input variables that were measured, or estimated from measured values, included ceiling height (H), floor area (A_{fl}), house volume (V), deposition rate of pesticide adhered to particles ($D_{f\_part}^{p}$), mass loading on the floor (M_{fl}), outdoor total suspended particle (TSP_o), bifenthrin concentration in outdoor air adhered to particles ($C_{air\_part}^{p}$), bifenthrin concentration in outdoor total suspended particles (C_{tspo}^{p}) bifenthrin concentration in soil (C_{s}^{p}), and bifenthrin concentration of organic matter in soil (C_{s}^{om}). Air exchange rate (Ach) was not measured in the current study, so the percentile distributions for homes in the United States reported by season and geographical region in Pandian et al. (1998) were referenced.

In order to determine the best-fit underlying distribution of each variable, a combination of visual and statistical methods were used. Histogram and cumulative distribution function (CDF) plots were used to visualize each input variable, and the potential distributions (e.g., normal, lognormal, Weibull) were overlaid to graphically suggest the best-fit distribution for each input variable. Based on the suggested best-fit distribution from the graphical methods, a Kolmorgorov-Smirnov (K-S) Goodness of Fit test was additionally used to test the suspected best-fit distribution. The K-S test is based on comparing the empirical distribution function with a hypothesized distribution function and determining the largest distance between the two functions. A p-value of > 0.05 fails to reject the null hypothesis that the data follow the hypothesized distribution, and therefore, justifies that distribution to be considered the best-fit distribution. The K-S test was chosen for the following reasons: (1) it is a non-parametric test and can be used with a small sample size; (2) it is used for continuous distributions and; (3) the K-S test statistic has the same distribution under all continuous distributions and thus, the K-S test statistic is not dependent on the underlying CDF function being tested.

For input variables referenced from the literature, in which only a minimum and maximum were reported, a uniform distribution was assumed. Additionally, the decay constant (k), which was computed from a range of soil half-lives, was also fitted with a uniform distribution. Please note that a best-fit distribution was not determined for the pesticide concentration in TSP_o (C^p_{tspo}) because this variable was calculated directly from simulated values for pesticide concentration in airborne particles ($C^p_{air\_part}$) and outdoor total suspended particles (TSP_o). In addition, a best-fit distribution was not determined for volume of the house (V) because this variable was calculated directly from the simulated values for area of the floor (A_{fl}) and ceiling height (H).

Variables that followed normal and lognormal distributions were truncated at the minimum value -5% and maximum value +5%. However, the one exception to this method was for concentration variables. For these variables, random values for the percentage of ND values were truncated at zero and the minimum detection limit (MDL), and random values for the percentage of detectable values were truncated at the MDL and the maximum concentration. The random values in relative proportions of non-detects and detects were then combined to generate a distribution. The transport parameters, previously determined in Layton and Beamer (2009a) (Table 3-1), were applied as fixed values.

For variables that followed a normal distribution, the underlying distribution was parameterized using the mean (m) and standard deviation (sd) of the data, while for variables that followed a lognormal distribution, the underlying distribution was parameterized using the geometric mean (gm) and geometric standard deviation (gsd). When only minimum and maximum values were available, these values were used to develop a uniform distribution.

The input variables used to solve for C_{fl}^{p} and the best-fit distributions can be viewed in Table 3-4.

3.2.5.3 Determining the Number of Iterations for the Monte Carlo Simulation and Running the Simulation

It was necessary to determine the number of iterations (i.e., number of random samples taken from along the distribution) (n_i) necessary for the Monte Carlo simulations. Equation 3-17 was used to estimate n_i, which is a probability-based approach that estimates, at a certain confidence level, the number of iterations needed based on the sample mean and variance (Driels and Shin, 2004).

$$Equation\ 3-17: \quad n_i = \left[\frac{100 \cdot t_c \cdot S_x}{E \cdot \bar{x}}\right]^2$$

t_c is the confidence coefficient from a two-tailed t-distribution, which is a referenced value (Driels and Shin, 2004; Pardoe, 2006). Please note that the confidence coefficient is generally taken from a normal distribution, but for a small sample size (~ <25), it is recommended to use a t-distribution, which has a similar shape as the normal distribution, but incorporates degrees of freedom, which is the sample size minus one (ibid). As the degrees of freedom increase, the t-distribution becomes closer to the normal distribution. In this case, 20 degrees of freedom (based on the sample size of 21) was used and a 99% confidence level was chosen.

$\bar{x}$ is the mean of the samples, x_i, with n numbers, which is estimated using Equation 3-18 (Driels and Shin, 2004).

$$Equation\ 3-18: \quad \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{1}{n}(x_1 + x_2 + \cdots + x_3)$$

S_x is the sample variance, which is estimated using Equation 3-19 (Driels and Shin, 2004).

$Equation\ 3-19$:

$$S_x = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n-1}[(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \cdots + (x_n - \bar{x})^2]$$

E is the percentage of error of the mean, which is 1%, given a 99% confidence level (Driels and Shin, 2004).

C_{fl}^{p} was estimated using the necessary number of iterations (n_i) for each input variable. Two additional methods were used to ensure that that the number of iterations chosen for the simulation was appropriate by testing the stability of the determined value of n_i.

First, the simulation (sim) was run to estimate C_{fl}^{p} the following two ways: (sim1) using the determined number of iterations (i.e., n_i) and (sim2) using 10-fold more than n_i (i.e., $n_i \cdot 10$). It was rationalized that if (n_i) had reached the appropriate number of iterations to make accurate predictions, then there should be no significant difference between the results of C_{fl}^{p} for sim1 and sim2. A two-sample Kolmorgorov-Smirnov (K-S) test was used to compare sim1 and sim2. The null hypothesis of the two-sample K-S test is that the two samples come from the same continuous distribution at an alpha-level set to 0.05.

Second, the simulation using the determined number of iterations (n_i) (i.e., sim1) was run three times (i.e., run1, run2, run3) in order to test the stability of the results. It was rationalized that if (n_i) produced stable results for C_{fl}^{p}, then there should be no significant difference between the results of C_{fl}^{p} for run 1, run2, and run3. Two-sample Kolmorgorov-Smirnov (K-S) tests were used to compare the results of each pair of runs.

3.2.5.4 Comparing Estimated and Measured Values of C_{fl}^{p}

In order to ultimately evaluate the proper functioning of the pesticide transport model, the estimated bifenthrin C_{fl}^{p}values were compared to the measured bifenthrin C_{fl}^{p}values using a one-sample t-test in which the mean of the measured C_{fl}^{p} was compared to the mean of the estimated C_{fl}^{p}. Both the estimated and measured C_{fl}^{p}were transformed to natural log concentrations prior to the statistical test because the C_{fl}^{p} concentrations were determined to be lognormally distributed based on a combination of the graphical fitting methods and the Kolmorgorov-Smirnov (K-S) test. The null hypothesis was that there was no difference between the estimated and measured floor dust concentrations, which was rejected at an alpha level of 0.05. Please see Appendix A for the complete code for RStudio to perform the model evaluation.

3.2.6 Computing Relative Contributions of Pathways

Once evaluation of the pesticide transport model was completed, and it was confirmed that the model was working, the relative contributions of air infiltration (IN_{air}^{p}) and soil track-in (IN_{track}^{p}) were estimated stochastically (i.e., using n_i) for both bifenthrin and permethrin, according to Equations 3-20 and Equation 3-21. The complete code for RStudio to estimate the relative contributions of each pathway can be viewed in Appendix B.

$$Equation\ 3-20: \quad IN_{air}^{p} = \frac{Ach \cdot P \cdot H \cdot C_{air\_part}^{p}}{\overline{\upsilon_o} \cdot Ach \cdot H} (\overline{\upsilon_o} \cdot A_{fl})$$

$$Equation\ 3-21: \quad IN_{track}^{p} = C_{s}^{p} \cdot T_{s}$$

3.2.7 Computing Residence Times

The residence time (τ_{fl}^{s}) equation from the soil contaminant transport model (Equation 3-5) was updated to represent residence time of pesticides in house dust (τ_{fl}^{p}), which can be seen in Equation 3-22. τ_{fl}^{p} incorporates the mass entering into the home and the rate at which the mass leaves the home through exfiltration (OUT_{exf}), cleaning (OUT_{cln}), and chemical decay (OUT_{decay}). Rates of removal through exfiltration, cleaning, and chemical decay can be seen in Equation 3-23 – Equation 3-25, respectively. A list of all variables, and how they were obtained, can be seen in Table 3-4. All residence time values were estimated stochastically (i.e., using n_i).

The complete code for RStudio to estimate residence times of bifenthrin and permethrin can be viewed in Appendix B.

$$Equation\ 3-22{:}\quad \tau_{fl}^{p} = \frac{(C_{air\_part}^{p} \cdot A_{fl} \cdot H) + (C_{fl}^{p} \cdot M_{fl} \cdot A_{fl})}{OUT_{exf} + OUT_{cln} + OUT_{decay}}$$

$$Equation\ 3-23{:}\quad OUT_{exf} = \frac{M_{fl} \cdot C_{fl}^{p}}{\overline{\upsilon_r} + Ach \cdot H} \cdot Ach \cdot H \cdot A_{fl}$$

$$Equation\ 3-24{:}\quad OUT_{decay} = k \cdot A_{fl} \cdot M_{fl} \cdot C_{fl}^{p}$$

$$Equation\ 3-25{:}\quad OUT_{cln} = Cln \cdot A_{fl} \cdot M_{fl} \cdot C_{fl}^{p}$$

Table 3-4: Input Variables to Stochastically Estimate τ_{fl}^{p}, OUT_{exf}, OUT_{decay}, and OUT_{cln}

Variable	Variable Explanation	Method to Obtain
A_{fl}	Floor area (m^2)	Measured for each home
Ach	Air exchange rate (d^{-1})	Referenced percentile distributions (Pandian et al., 1998) and calculated gm and gsd
Cln	Cleaning rate (d^{-1})	Assumed to 0.0053 (Layton and Beamer, 2009
$C_{air\_part}^{p}$	Concentration of pesticide adhered to particles in outdoor air (µg/g)	Outdoor air measured for each home and portion adhered to particles calculated (Equation 3-7/Equation 3-9)
C_{fl}^{p}	Concentration of pesticide in floor dust (µg/g)	Measured for each home
H	Ceiling height (m)	Measured for each home
k	First-order pesticide decay rate (d^{-1})	*k* calculated (Equation 3-11) using range of soil half-lives referenced from peer-reviewed literature
M_{fl}	Mass loading of pesticides on particles onto floor surface (g/m^2)	Measured for each home
R	Resuspension rate of pesticides adhered to floor particles into indoor air (d^{-1})	Assumed to be 0.011 (Layton and Beamer, 2009)
$\overline{\upsilon_o}$	Deposition velocity of outdoor-derived pesticides adhered to particles settling onto floor (m/d)	Assumed to be 135-234 (Thatcher and Layton, 1995)

3.3 Results

3.3.1 Outdoor Air Sample Partitioning onto Particles and into Vapor Phase

The octanol-air partition coefficient (K_{OA}) was determined to be 2x10^{10} for bifenthrin and 2x10^{10} for permethrin based on Equation 3-10, using the ideal gas constant (R) of 8.314 Pa·m^3/K·mol, the average temperature across all sampling periods (T), which was 293 K, and referenced values for the octanol-water partitioning coefficient (K_{OW}) and Henry's Law Constant (H) (ATSDR, 2003; MacKay et al., 1997; Krieger and Kriege, 2001). The variables inputs and outcomes for K_{OA} can be viewed in Table 3-5.

Table 3-5: Input Variables and Outcomes for K_{OA} of Pesticides

Pesticide	*Variable*				
	R $(\frac{Pa \cdot m^3}{K \cdot mol})$	T (K)	H [(a,b)] $(\frac{Pa}{m^3 \cdot mol})$	K_{OW} [(b,c)]	K_{OA}
Bifenthrin	8.314	293	7x10^{-4}	1x10^6	2x10^{10}
Permethrin			4x10^{-2}	3x10^5	2x10^{10}

[a]*ATSDR, 2003;* [b]*MacKay et al., 1997;* [c]*Krieger and Kriege, 2001*

The partition coefficient (K_P) was determined to be 0.600 for bifenthrin and 0.004 for permethrin, based on Equation 3-9, in which 14% was assumed for the fraction of organic matter (f_{om}) (see methods section for how this value was established) and the previously determined K_{OA} values (Table 3-5) were used. The total suspended particles (TSP) were assumed to be 20.9 g/m^3 based on the mean value from the SH study. The percent of partitioning onto particles (ϕ) for outdoor air samples was determined to be 93% for bifenthrin and 8% for permethrin based on Equation 3-7, and the percent of partitioning into the vapor phase (γ) was determined to be 7% for bifenthrin and 92% for permethrin based on Equation 3-8. The input variables and outcomes for pesticide partitioning in the particle-phase and vapor-phase can be seen in Table 3-6.

Table 3-6: Input Variables and Outcomes for Pesticide Partitioning into Particle-Phase (ϕ) and Vapor Phase (γ)

Pesticide	***Variable***				
	f_{om} (%)	K_P	TSP ($\frac{g}{m^3}$)	ϕ (%)	γ (%)
Bifenthrin	14	*0.600*	20.9	*93*	*7*
Permethrin		*0.004*		*8*	*92*

3.3.2 Pesticide Decay Rate and Indoor Half-life

Based on the range of soil half-lives reported as 65-125 days for bifenthrin (WHO, 2011) and 11-113 days for permethrin (Imgrund, 2003), along with the decision to use these values as the indoor half-life (see methods for reasoning behind this decision), the range of decay constant (k) was computed to be 0.006-0.0107 d^{-1} for bifenthrin and 0.006-0.0598 d^{-1} for permethrin based on Equation 3-11.

3.3.3 Pesticide Transport Model Evaluation

The best-fit distributions and parameterization values for each input variable to estimate C_{fl}^{p} can be seen in Table 3-7. Please see Appendix C for histograms and CDF plots, along with K-S test results, which were all used for deciding the best-fit distribution of each input variable.

Table 3-7: Fitted Distributions and Parameterization Values for Input Variables to Stochastically Evaluate and Run Pesticide Transport Model

Variable	Best-Fit Distribution	Parameterization Values	
A_{fl}	Lognormal	gm=4.69; gsd=0.48	
Ach	Lognormal	gm= 14.76; gsd= 0.76	
C_s^{om}	Lognormal	gm=-3.07; gsd = 0.35	
C_s^p	Lognormal	*Bifenthrin:* gm=-4.04; gsd=0.70	*Permethrin:* gm= -2.63; gsd= 1.43
H	Normal	m=2.56; sd=0.25	
k	Uniform	*Bifenthrin:* min=0.006; max=0.01	*Permethrin:* min=0.006; max=0.06
M_{fl}	Lognormal	gm=0.86; gsd-=1.54	
$C_{air\_part}^p$	Lognormal	*Bifenthrin*: gm=-7.32; gsd=0.81	*Permethrin*: gm=-10.64; gsd=0.56
P	Uniform	min=0.90; max=1	
TSP_o	Lognormal	gm=-10.62; gsd= 1.21	
$\overline{\upsilon_o}$	Uniform	min=14; max=26	
$\overline{\upsilon_r}$	Uniform	min= 135; max=234	

m=mean; sd= standard deviation;
gm=geometric mean; gsd= geometric standard deviation

Using the probability-based approach to estimate the number of necessary iterations (n_i), the sample mean ($\bar{x}$) was estimated to be 0.24 and the sample variance (S_x) was estimated to be 0.27. The referenced confidence coefficient from the two-tailed t-distribution (t_c) was 2.086 (Driels and Shin, 2004; Pardoe, 2006) and the error (E) was 1% given the 99% confidence level. The necessary number of iterations (n_i) was estimated to be 55,072.

Results of the K-S tests comparing sim1 and sim2 showed no significant difference was between 55,072 and 550,720 simulations (p= 0.14). There were also no significant differences of the K-S tests comparing run1 and run2 (p=0.88), run1 and run3 (p=0.90), or run2 and run3 (p=0.84) when using 55,072 for n_i. As such, 55,072 iterations were deemed to be an appropriate value for n_i.

The one-sample t-test, used to test whether there was a significant difference between the mean of the measured and estimated C_{fl}^{p} values, yielded a p-value of 0.17. The null hypothesis that there was no difference between the estimated and measured C_{fl}^{p} failed to be rejected, and thus the model was considered to be successfully evaluated. The natural log of the concentration of the model estimated C_{fl}^{p} (n=55,072) and the measured C_{fl}^{p} (n=21) can be seen in Figure 3-3.

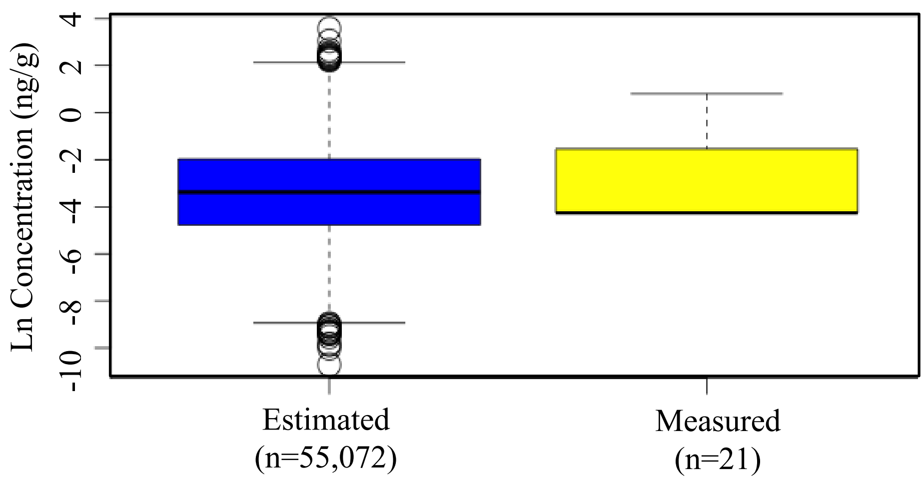


Figure 3-3: Box Plots of Natural Log Concentrations of Bifenthrin in House Dust Estimated by the Model (Blue) Compared to Measured (Yellow) with p-value of One-sample T-test Between the Mean of Estimated and Measured Concentrations

3.3.4 Pathway Contributions and Residence Times

The relative contributions of air infiltration (%) and soil track-in (%) for bifenthrin and permethrin can be seen in Figure 3-4 and Figure 3-5, respectively. The percentile distributions for the relative contributions (%) for each pesticide, along with the residence times (days) for each pesticide can be viewed in Table 3-8.

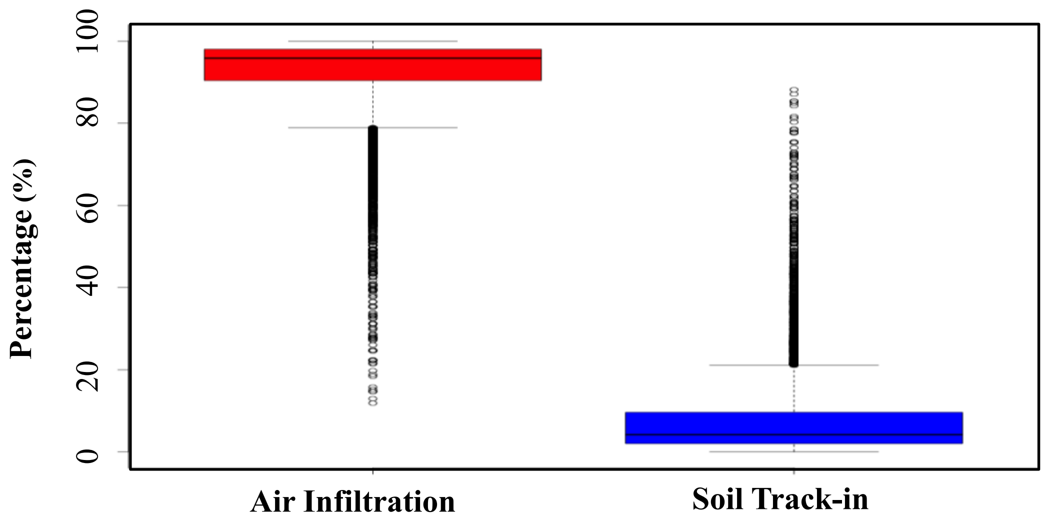


Figure 3-4: Relative Contributions (%) of *Bifenthrin* into the House Dust via Air Infiltration (Red) and Soil Track-in (Blue)

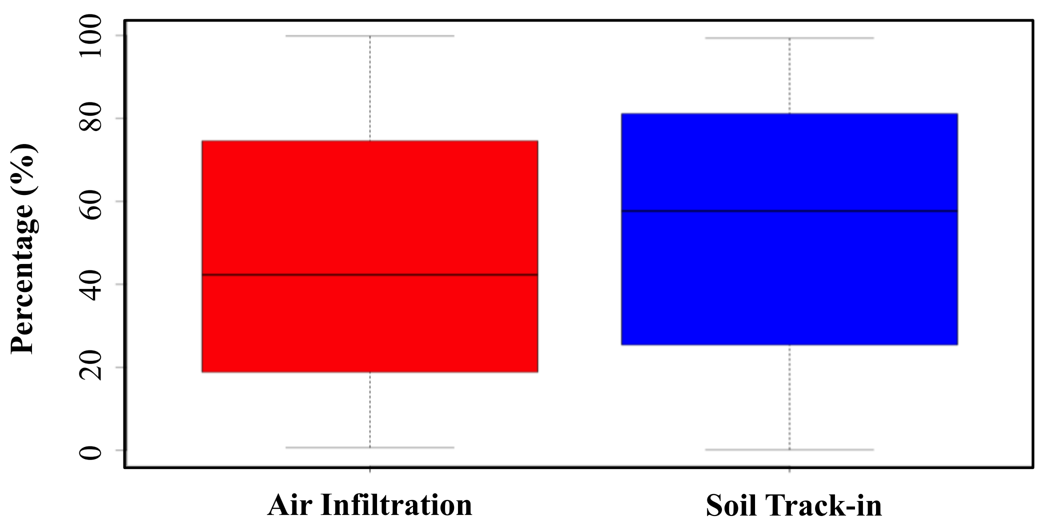


Figure 3-5: Relative Contributions (%) of *Permethrin* into the House Dust via Air Infiltration (Red) and Soil Track-in (Blue)

Table 3-8: Percentile Distributions of Air Infiltration and Soil Track-in and Residence Time of Pesticides (n=55,072)

Pesticide	**Model Results**	**Percentile Distribution (%)**				
		5th	**25th**	**50th**	**75th**	**95th**
Bifenthrin	Air Infiltration (%)	70.18	90.28	95.68	97.99	99.30
	Soil Track-in (%)	0.70	2.01	4.31	9.72	29.82
	Residence Time (d)	<1	1	5	19	132
Permethrin	Air Infiltration (%)	5.13	18.15	42.13	74.37	94.46
	Soil Track-in (%)	5.54	25.63	57.87	81.85	94.86
	Residence Time (d)	16	20	27	42	72

3.4 Discussion

3.4.1 A Properly Functioning Pesticide Transport Model

In the current study, the author was able to successfully develop, evaluate, and apply a modeling framework that can be used to assess the transport of agricultural pesticides into a residential environment. This pesticide transport model effectively builds upon a previous soil contaminant transport model developed by Layton and Beamer (2009). The pesticide transport model developed for the current study now allows pesticide researchers to estimate the relative contributions of the air infiltration and soil track-in pathways of agricultural pesticides from fields into the house dust.

The need to better understand pesticide transport from agricultural fields has been mentioned repeatedly as an important component of disentangling the complex issue of increased detection of agricultural pesticides in farmworkers' homes (Simcox et al., 1995; Richards et al., 2001; Fenske et al., 2002; Quandt et al., 2004; Weppner et al., 2006). This is the first study, to the knowledge of the author of this dissertation, to quantify the relative contribution of each relevant pathway, offering a major step forward in being able to effectively address the issue of agricultural pesticide transport into homes.

3.4.2 Explanation for Ineffective Previous Interventions

One of the major motivations of the current study was to explore possible reasons for the limited success of previous interventions that aimed to reduce pesticide levels in the house dust of farmworkers' homes, particularly the Para Niños Saludables intervention that successfully changed farmworkers' behaviors related to the soil track-in pathway, yet was unable to observe any reduction of pesticide levels in the house dust from the homes of farmworkers or in the urine of their children (Thompson et al., 2008; Strong et al., 2009).

Overall, results of the current study showed that air infiltration accounted for the vast majority of the contribution to the house dust for bifenthrin and a lower, yet still notable, proportion for permethrin. It is possible that the Para Niños Saludables intervention (ibid) did not observe reductions in pesticide levels because the intervention did not target air infiltration, a prominent pathway of agricultural pesticides into the house dust. It is likely that variation in relative contributions of air infiltration and soil track-in is related to the inherent differences among the pesticides rooted in their chemical characteristics. For example, the fact that the median contribution to house dust from the air infiltration pathway was higher for bifenthrin (95.68%) compared to permethrin (42.13%) can be at least partially attributed to the fact that bifenthrin is a more persistent pesticide and has a stronger adherence to soil particles compared to permethrin (a thorough description of chemical characteristics of bifenthrin and permethrin can be seen in Chapter 4).

The soil track-in pathway can range from partially relevant to almost inconsequential in its contribution of agricultural pesticide levels in the house dust, depending on the pesticide of interest. In the current study, the median contribution from soil track-in was 10-fold higher for permethrin (57.87%) compared to bifenthrin (4.31%). The fact that the relative contributions of air infiltration and soil track-in can vary may shed light on the mixed suggestions in previous studies related to the transport pathway of pesticides from agricultural fields to homes. For example, some studies such as McCauley et al. (2003), Curwin et al. (2005), and Lozier et al. (2012) reported evidence of the soil track-in pathway, while others such as Quandt et al. (2004), Weppner et al. (2006), and Gunier et al. (2011) suggested pesticide drift into the home via air infiltration. With such a great diversity among pesticides, and the subsequent variation in the relative contributions via air infiltration and soil track-in to the house dust, researchers are encouraged to make an effort to understand which pesticides are of concern in the agricultural community of interest prior to designing interventions.

Results of the current study estimated the residence time of pesticides in the house dust to be within one year for both bifenthrin and permethrin (i.e., median residence time was 5 days for bifenthrin and 27 days for permethrin). These results suggest that the residence time of pesticides in the house dust is not likely to be the driving force behind the lack of reduced pesticide levels in the Para Niños Saludables intervention (Thompson et al., 2008; Strong et al., 2009). The residence times computed in the current study are similar to multiple previous estimations of residence time for particles in the home (Allott et al., 1994; Qian et al., 2008; Layton and Beamer, 2009). On the other hand, the residence times in the current study are quite different to that of Shin et al. (2013), which reported residence times of multiple years for various pesticides. It should be noted that, according to Shin et al. (2013), indoor air and house dust are considered "mobile phases" of pesticides in the home, meaning that they can easily be removed through cleaning. Shin et al. (2013) proceeded to additionally point out that a "non-mobile" phase may also exist, particularly in the carpet fibers and the pad beneath the carpet, where mechanical cleaning processes may not effectively remove pesticides (Ferguson et al., 2008; Shin et al., 2013). In Shin et al. (2013), when both the "mobile phase" and "non-mobile phase" were taken into account, the residence time for permethrin at steady-state was reported to be 3.9 years, which is more than fifty times the residence time estimated in the current study. Bifenthrin was not included in Shin et al. (2013), but it can be gleaned that had it been included, bifenthrin's estimated residence time would be similar to that of permethrin.

The current study was not been designed to capture the "non-mobile" phase because samples from floor dust did not differentiate between hard flooring and carpet and because indoor air samples were not collected. Accordingly, it would be wise to consider the residence times computed in the current study with caution. It is not possible to say with certainty that the residence time of agricultural pesticides in the house dust did not at all contribute to the lack of reduction of pesticide levels in the Para Niños Saludables intervention (Thompson et al., 2008; Strong et al., 2009), particularly for the homes with carpeting. In the future, researchers may choose to design their study so that dust samples are taken separately from hard flooring and carpet in order to capture both the “mobile” and “non-mobile” phases in the floor

3.4.3 Unique Contribution of Assessing Air Infiltration of Pesticides Adhered to Soil Particles

One notable aspect of the current study is the understanding that air transport and subsequently, air infiltration, is not limited to pesticides in the vapor phase. For most studies in the peer-reviewed literature, the discussion of air transport has been limited to that of pesticide spray drift (MacNeil and Hikichi, 1986; Anderson and Hites, 1989; Fox et al., 1990; Simcox et al., 1995; Nishioka et al., 1996; Loewenherz et al., 1997; Richards et al., 2001; Coronado et al., 2011). Although particle transport through the ambient air has been established for many years (Cohen and Pinkerton, 1966; Wadleigh, 1968; Bidleman and Olney, 1975; El-Shobokshy and Hussein, 1988), the contribution of pesticides adhered to soil particles transported through the air, and into the home via air infiltration, has not been widely discussed. There has been some general mention of pesticide transport via adherence to soil particles in the peer-reviewed literature (Bidleman, 1999; Nishioka et al., 1999a; Lu et al., 2000; Quandt et al., 2004; Scheyer et al., 2007), but these studies did not actually include an assessment of air infiltration. Through the development of the current study’s modeling framework that focused solely on agricultural pesticides adhered to soil particles, the author was able to demonstrate the relevance of soil resuspension and wind-driven transport of agricultural pesticides into the house dust.

The findings of the current study are congruent with the results of the application of the original soil contaminant transport model by Layton and Beamer (2009), which found that more than 85% of arsenic and lead entered the home, and contributed to the house dust, through air infiltration (Beamer et al., 2009a). The results of the application of the modified soil contaminant transport model (i.e., the pesticide transport model), which accounted for processes relevant to pesticides (i.e., partitioning between soil particles and the vapor phase, along with chemical decay), highlights the phenomenon that wind resuspension of contaminated particles is a concern even for semi-volatile organic compounds. Even in the case of permethrin, where only 8% was calculated as particle-bound, a median of 42.13% entered the home through air infiltration, contributing to the house dust. Pesticides with a higher level of partitioning onto particles result in an even greater percentage of house dust contribution via air infiltration, as could be seen for bifenthrin, which had 93% adherence to particles and a median of 95.68% contribution to the house dust via air infiltration. Wind resuspension of contaminated particles is particularly concerning in desert communities, such as Yuma County, Arizona, which is known for dusty and windy conditions. Looking towards the future, it is reasonable to believe that global climate change may cause communities, like Yuma County, Arizona, to only increase in dustiness and windiness, further enhancing resuspension of pesticide-contaminated soil particles in outdoor air, thereby increasing air infiltration of pesticides into nearby homes.

3.4.4 Contributions of Pesticides in the Vapor Phase to Indoor Air

It should be noted that the current modeling framework excludes contribution of pesticides in the vapor phase to the house dust because it was assumed that pesticides in this phases remain in the air, contributing very minimally to house dust. Since air infiltration in the current study only considered contribution to the indoor houses dust and does not include contribution to the indoor air, it is interesting to realize that the estimated contribution through air infiltration is an underestimated contribution to the overall indoor environment. This is particularly relevant for permethrin, where 92% was estimated to partition into the vapor phase, which can also infiltrate into the home, but would remain largely in the indoor air rather than settle in the house dust. For pesticides that significantly partition into the vapor phase, there is concern for inhalational exposure in addition to non-dietary ingestion of house dust. This understanding only further enhances the significance of the air infiltration pathway. In future studies, it would be useful to include indoor air sampling to capture the contribution of pesticides to the indoor air via air infiltration.

3.4.5 Issues of Environmental Justice

The results of the current study highlight environmental justice issues faced by farmworkers and their families. The current study's population was limited to farmworker families because there is strong evidence that there are higher levels of agricultural pesticides in their house dust compared to non-farmworker families (Simcox et al., 1995; Bradman et al., 1996; Lu et al., 2000; McCauley et al., 2001; Fenske et al., 2002; Quirós-Alcalá et al., 2011). It should be noted that in previous studies of sampled homes in agricultural communities, agricultural pesticides could be detected in both farmworkers' home and non-farmworkers' homes, though the levels were consistently higher in the farmworkers' homes (Simcox et al., 1995; Bradman et al., 1996; Fenske et al., 2002). A valuable future study could be the application of the current modeling framework to datasets that include both farmworker and non-farmworker homes. To the knowledge of the author of this dissertation, no such dataset currently exists, and therefore, new sampling initiatives would need to be designed and implemented to meet this initiative.

In the current study, the discovered significance of the air infiltration pathway implies that there is a community-wide concern with respect to increased agricultural pesticide levels in house dust because pesticides applied in nearby fields may infiltrate into homes, and this is not contingent upon working in the agricultural fields. The prominence of the air infiltration pathway is congruent with the findings of Chapters 5 and 6 of this dissertation, where it is reported that a closer distance between the home and nearest agricultural field was positively associated with agricultural pesticide levels in the house dust, namely for bifenthrin. The relevance of proximity to the nearest field has been reported in many other studies as well (Simcox et al., 1995; Loewenherz et al., 1997; Lu et al., 2000; McCauley et al., 2001; Richards et al., 2001; Fenske et al., 2002; Quandt et al., 2004; Weppner et al., 2006) A review of these studies is more thoroughly discussed in Chapter 5.

3.4.6 Insight into Developing Future Interventions

Prior to developing interventions to reduce agricultural pesticide levels in house dust, it is undoubtedly necessary to consider the major pathway(s) in which these pesticides enter the home. In agricultural communities akin to Yuma County, Arizona, where thousands of pesticides are applied annually (Sugeng, 2012; Sugeng et al., 2013), the task of prioritizing pesticides to target for sampling, and subsequent modeling, is challenging. In Chapter 2 of this dissertation, the use of a pesticide hazard ranking system was found to be a useful method of identifying relevant pesticide hazard priorities in the agricultural community of interest.

For researchers who seek to develop interventions in agricultural communities to reduce agricultural pesticide levels in the home, it is suggested that researchers use both the pesticide hazard ranking system described in Chapter 2 to identify the most relevant pesticide hazards and the model from the current Chapter to compute the relative contributions of pesticide pathways. These strategies will provide insight into which pathway(s) should be targeted. For example, if it is revealed that the overwhelming majority of the relevant pesticides enter the home primarily through air infiltration, it would be wise to focus on interventions related to the air infiltration pathway, such as making changes to heating or cooling of the home. If it is revealed that soil track-in remains a notable pathway of pesticides into the home, it may be sensible to target this pathway through efforts such as placing mats outside and inside of the doors. Households that include farmworkers may include some additional contribution via the soil track-in pathway (McCauley et al., 2003; Harnly et al., 2009), and therefore, continued targeting of the take-home pathway/soil track-in pathway ,in addition to targeting the air infiltration pathway, is reasonable. It is important to mention that not all soil track-in is necessarily limited to behaviors of farmworkers. Rather, it is possible that pesticides from agricultural fields are transported through the air via the wind and settle in the outdoor yard soil of homes. In this scenario, all family members can track contaminated soil from outside into the home. As such, expanding the focus of soil track-in to include behaviors of the entire household, rather than solely the farmworkers, may also improve the effectiveness of interventions aimed at decreasing agricultural pesticide levels in the home.

It would be best to target both the air infiltration and soil track-in pathways since both contribute, to some degree, to agricultural pesticide levels in the home. However, from a research perspective of being able to evaluate the effectiveness of an intervention, it would not be wise to implement multiple changes at one time, particularly when the changes include targeting more than one transport pathway. Given the fact that the soil track-in pathway has previously been targeted with limited, and that the current study has been able to illustrate the overwhelming significance of an alternate pathway, air infiltration, it is recommended that researchers begin to prioritize interventions targeting the air infiltration pathway.

3.4.7 Conclusions

A modeling framework used to assess the transport of pesticides from agricultural fields into the house dust was developed, evaluated, and applied in this Chapter. This is the first study that has quantified the relative contributions of the air infiltration and soil track-in pathways of agricultural pesticides into the house dust, offering a step forward in addressing the issue of increased agricultural pesticides in farmworkers' homes and fulfilling the first major aim of this dissertation.

In the current study, air infiltration contributed to a median of 95.68% of bifenthrin in the house dust, while soil track-in only contributed to 4.31% of bifenthrin in the house dust. For permethrin, air infiltration contributed to a median of 42.13% of the house dust level, while soil track-in accounted for 57.87% of the house dust level. It should be noted that permethrin is likely to also infiltrate into the home in the vapor phase, contributing to the indoor air level, but this could not be captured in the current study. The finding that air infiltration is a major pathway of both pesticides into the house dust of farmworkers' homes confirms the first hypothesis of the first major aim of this dissertation. It is possible that the Para Niños Saludables intervention was unable to reduce pesticide levels in the house dust of farmworkers' homes because they did not take the air infiltration pathway into consideration. It is recommended that future intervention studies target factors related to the air infiltration pathway.

The median residence time for each pesticide in the house dust was quite short, as bifenthrin was found to have a median of 5 days and permethrin was found to have a median of 27 days. It does not appear, from the results of this study, that the residence time of pesticides was a significant reason for the lack of reduced pesticide levels in the previous Para Niños Saludables intervention. However, this conclusion should be approached with caution because the current study was not equipped to distinguish carpeted floors, a media that makes removal of pesticides more difficult, and could possibly cause the residence time to be higher.

CHAPTER 4

IDENTIFYING EXTERNAL RISK FACTORS THAT INFLUENCE AGRICULTURAL PESTICIDE LEVELS AT FARMWORKERS' HOMES

4.1 Introduction

Previously, there have been many studies that assessed pesticide levels at farmworkers' homes (McCauley et al., 2001; Curl et al., 2002; Thompson et al., 2003; Rothlein et al., 2006; Arcury et al., 2007; Bradman et al., 2007; Harnly, 2009; Quirós-Alcalá et al., 2011; Bradman et al., 2011; Thompson et al., 2014; Arcury et al., 2014). Limited studies have investigated the effect of factors that are not directly related to the farmworkers', or their household, on the detected pesticide levels at their homes (Harnly, 2009; Quirós-Alcalá et al., 2011). Such studies have previously investigated the effect of regional pesticide applications (Harnly, 2009; Quirós-Alcalá et al., 2011) and weather conditions in the days prior to sampling (Harnly, 2009) on pesticide levels at farmworkers' homes. Overall, there remains a lack of strong identification and characterization of factors not directly related to the farmworkers, or their household, that may influence agricultural pesticide levels at their homes. For the purposes of this dissertation, such factors can be referred to as "external risk factors" because they are external to the farmworkers and their household.

The second major aim of this dissertation seeks to improve the identification and characterization of external risk factors, by assessing the association between the results of pesticide sampling at the farmworkers' homes with a variety of factors. Among the possibly influential external risk factors are the inherent chemical characteristics of pesticides applied in the agricultural community, specific microclimate/weather conditions during the sampling period, and the spatial and temporal distributions of the pesticide applications near the farmworkers' homes. The main hypotheses for the second major aim of this dissertation were that: (1) chemical characteristics are associated with the detection frequency of pesticides in the outdoor air, yard soil and house dust, and (2) the microclimate/weather conditions during the time of sampling, along with spatial and temporal distributions of agricultural pesticide applications near the participants' homes prior to sampling, are most strongly associated with the detection of pesticides in the outdoor air.

The inherent chemical characteristics may provide important information about the likelihood that the pesticides will be detected in the environment at farmworkers' homes post-application to nearby agricultural fields (Wauchope et al., 1992). Chemical characteristics vary drastically from pesticide to pesticide, highlighting the importance of knowing which pesticides are relevant to an agricultural community of interest There are multiple databases and handbooks designed to describe the chemical characteristics of pesticides, such as their vapor pressure, soil adsorption, and soil half-life, and these resources can aid in understanding the factors that drive pesticide persistence and movement in the environment (Wauchope et al., 1992; MacKay et al., 2006; USEPA, 2014b). Understanding chemical characteristic of the relevant pesticides could provide insight into the pathways of pesticides from agricultural fields to nearby homes. For example, pesticides with a high vapor pressure are expected to be transported through the air in the vapor phase, while those with a low vapor pressure would be expected to adhere to particles and be transported either through the air as resuspended soil or through track-in of contaminated soil on shoes, clothes, and skin.

The microclimate/local weather conditions during the time of sampling should also be considered because it is well known that these conditions can influence the drift and deposit of chemicals in the outdoor environment (Bache and Johnstone, 1992; Akesson and Yates, 1964). Particularly in agriculture, weather conditions, such as wind speed, have long been explored from the perspective of pesticide application efficiency and safety (Bache and Johnstone, 1992). It would be useful to also explore microclimate/weather conditions from the perspective of health and safety in agricultural communities.

Spatial and temporal distributions of pesticide applications to agricultural fields in relation to the homes sampled may also significantly impact whether such pesticides can be detected at farmworkers' homes. A diverse array of pesticides is applied in the United States, with over 17,000 pesticide products being registered as of 2007 (Levine, 2007). As such, nationwide pesticide application trends may to be irrelevant to a specific agricultural community of interest. Geographic information systems (GIS) applications have been on the rise to better understand the spatial and temporal distribution of specific pesticides applications and to examine the association with exposure risk and health outcomes in agricultural communities (Gunier et al., 2001; De la Rosa et al., 2004; Ares et al., 2006, Posen et al., 2006; Luo et al., 2010).

4.2 Methods

4.2.1 Overview

The inherent chemical characteristics of the pesticides of interest, microclimate/local weather conditions during sampling periods, and the spatial and temporal distributions of pesticide applications nearby each farmworker's home, and throughout Yuma County, were investigated. All of these factors were assessed for association with pesticides detected at the farmworkers' homes.

The natural log of the pesticide concentrations was used for all analyses. Spearman's rank correlation tests, which determine the strength of a correlation on a scale of 0.00-1.00 as designated by the Spearman's r-value, were used. Interpretation of the Spearman's r-value is subjective, so the author of this dissertation used guidelines from basic statistics textbooks (Swinscow and Campbell, 200; Stewart, 2010). As such, the r-values in the current study were interpreted as follows: >0.40-0.59 as a moderate correlation, 0.60-0.79 as a strong correlation, and 0.80-1.00 as a very strong correlation. All Spearman's rank correlations were also tested for statistical significance at an alpha level of 0.05.

Please note that analyses in the current Chapter were limited to the pesticides that had a detection frequency of at least 25% for the specific media type. As such, analyses were only performed for bifenthrin, trifluralin and permethrin (cis and trans isomers combined). Due to low detection frequency, associations with trifluralin could not be assessed for the soil and house dust and associations with permethrin could not be assessed for the outdoor air.

4.2.2 Chemical Characteristics Assessment

Chemical characteristics of interest were researched for each pesticide. Values from textbooks grounded in extensive peer-reviewed literature (Krieger and Kriege, 2001; MacKay et al., 1997; Hayes and Lewis, 1991) were utilized as the preferable sources for these values. When multiple values were listed in the textbooks, a computed mean value was used since this is the most commonly used measure of central tendency. In the case where a value could not be found in any textbook, the Agency of Toxic Substances and Disease Registry (ATSDR) database was referenced (ATSDR, 2003).

Molecular weight (g/mol), soil half-life (days), vapor pressure at 25°C (mmHg), aqueous solubility at 25°C (mg/L), Henry's Law Constant at 25°C (K_H) ($Pa{\cdot}m^3/mol$), and log octanol-water coefficient (log K_{ow}) (unitless) were obtained from the peer-reviewed literature. Soil organic carbon-water coefficient (log K_{oc}) was calculated sing Equation 4-1 (USEPA, 1996) and the air-soil partition coefficient ($K_{air/soil}$) was calculated using Equation 4-2 (Holmén et al., 2013). A description of each of these chemical characteristics can also be viewed in Table 4-1.

$$Equation\ 4-1: \quad \log K_{oc} = 0.0784 + (0.7919 \cdot \log K_{ow})$$

$$Equation\ 4-2: \quad K_{air/soil} = \frac{K_H}{\log K_{oc}}$$

Table 4-1: Description of Chemical Characteristics

Chemical Characteristic	**Description**
Molecular weight (g/mol)	Mass of the chemical
Soil half-life (days)	Time until half of the chemical is broken down in soil
Vapor pressure at 25°C (mmHg)	Pressure exerted by vapor in thermodynamic equilibrium with its condensed phases in a closed system
Aqueous solubility at 25°C (mg/L)	Partitioning of a chemical between its pure phase and water at equilibrium
Henry's Law Constant at 25°C ($Pa \cdot m^3/mol$)	Based on Henry's Law, which is dependent on (1) inherent volatility, given by vapor pressure and (2) hydrophobicity, given by aqueous solubility
Octanol-water coefficient (log K_{ow}) (unitless)	Partitioning between liquid octanol and water
Soil organic carbon-water coefficient (log K_{oc}) (unitless)	Partitioning between organic carbon in soil and water
Air-soil partition coefficient ($K_{air/soil}$)	Partitioning between air in the vapor phase and soil

Spearman's rank correlations were used to assess associations between each of the chemical characteristics, as well as to determine whether there was a relationship between the measured detection frequency in the outdoor air, yard soil, and house dust and each pesticide's various chemical characteristics. Additionally, a Principal Component Analysis (PCA) was performed for the chemical characteristics of each pesticide in an attempt to identify which chemical characteristics are most influential on each pesticide, as well as which chemical characteristics are most similar to each other based on their chemical characteristics.

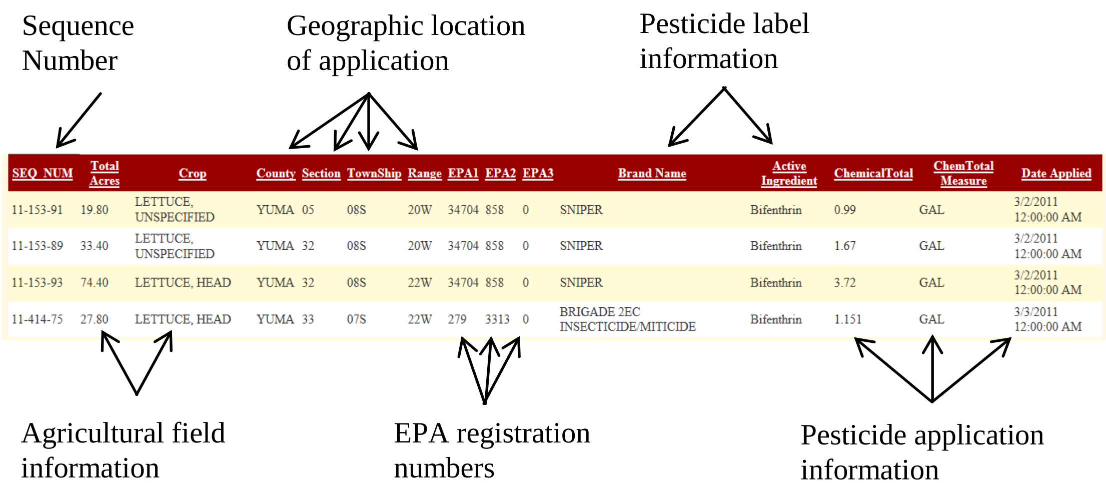
4.2.3 Microclimate/Weather Conditions During Sampling Assessment

Microclimate/weather conditions during the time of sampling were obtained from the National Weather Service database (NWS, 2014), which maintains historical weather data for various sampling stations within a given city. In the current study, the Yuma Marine Corp Station was used because it is the sampling station closest to the majority of the participants' homes. Conditions that were considered were total rainfall (inches), mean temperature (°F), mean humidity (%), and mean wind speed (mph).

Spearman's rank correlations first were used to assess associations between each of the microclimate/weather conditions. Then, Spearman's rank correlations were further used to assess the associations between the microclimate/weather conditions and the measured pesticide concentrations in outdoor air, yard soil, and house dust. A PCA was additionally performed for the average weather conditions during the sampling period for each household in order to examine which conditions were most influential and how the conditions interacted with each other.

4.2.4 Spatial and Temporal Assessment

Spatial and temporal associations between applications of each pesticide within one-year and one-month prior to sampling and within one-mile and half-mile circular buffers of the sampled farmworkers' homes were assessed. These associations were only performed for pesticides with 25% detection frequency in the given media (i.e., bifenthrin in soil, air, and dust; permethrin in soil and dust; trifluralin in air). The Arizona Department of Agricultural Pesticide Use "1080" Database, a publicly available database, was used to obtain records of agricultural pesticide applications throughout Yuma County (AZDA, 2014). Under Arizona Revised Statutes, Title 3, Article 6, a Grower/Pesticide Advisor is required to record agricultural pesticide applications to the Database. The Database provides the following: a sequence number (i.e., a number provided at the time of submission), information about the agricultural field to which the pesticide was applied (i.e., total acres and crop), geographic location of application (i.e., county, section, township, range), EPA registration numbers, pesticide label information (i.e., brand name, active ingredient), and pesticide application information (i.e., chemical total, chemical total measure, and date applied) (ibid) (Figure 4-1).



SEQ NUM	Total Acres	Crop	County	Section	TownShip	Range	EPA1	EPA2	EPA3	Brand Name	Active Ingredient	ChemicalTotal	ChemTotal Measure	Date Applied
11-153-91	19.80	LETTUCE, UNSPECIFIED	YUMA	05	08S	20W	34704	858	0	SNIPER	Bifenthrin	0.99	GAL	3/2/2011 12:00:00 AM
11-153-89	33.40	LETTUCE, UNSPECIFIED	YUMA	32	08S	20W	34704	858	0	SNIPER	Bifenthrin	1.67	GAL	3/2/2011 12:00:00 AM
11-153-93	74.40	LETTUCE, HEAD	YUMA	32	08S	22W	34704	858	0	SNIPER	Bifenthrin	3.72	GAL	3/2/2011 12:00:00 AM
11-414-75	27.80	LETTUCE, HEAD	YUMA	33	07S	22W	279	3313	0	BRIGADE 2EC INSECTICIDE/MITICIDE	Bifenthrin	1.151	GAL	3/3/2011 12:00:00 AM

Figure 4-1: Information Provided on the “1080” Database (AZDA, 2014)

ArcGIS v. 10.1 (ESRI, 2012) was used to map the one-mile and half-mile circular buffers around each home sampled. The total pounds of each pesticide applied within each square-mile section were overlaid on the circular buffers surrounding each home. When the pesticide applications within the buffer were part of more than one square-mile section, a spatially weighted average of pounds applied was computed to determine the pounds of pesticide per square mile using Equation 4-

3. This procedure was done for one-year and one-month time periods prior to sampling with the pesticide detections in yard soil, house dust, and outdoor air.

$$Equation\ 4-3: \quad SWA_{bw} = \frac{\sum_{i=1}^{n} P_i \cdot A_i}{\sum_{i=1}^{n} A_i}$$

Where: P_i is the amount of pesticide application (lbs) for the ith interval and A_i is the area in which the pesticide was applied (square mile) for the ith interval

4.3 Results

4.3.1 Associations with Chemical Characteristics

The chemical characteristics of each pesticide of interest can be viewed in Table 4-2. Unsurprisingly, many of the chemical characteristics were correlated with one another (Table 4-3). The chemical characteristics that were very strongly correlated with each other (r>0.80) were also the ones in which the correlation was statistically significant (p<0.05). As expected, log K_{ow} and log K_{oc} were perfectly correlated with each other (r=1.00). Log K_{ow} and log K_{oc} were also perfectly negatively correlated with aqueous solubility (r=-1.00). Molecular weight had a very strong positive correlation with log K_{ow} and log K_{oc} (r=0.83) and a very strong negative correlation with aqueous solubility (r=-0.83). Molecular weight also had a strong positive correlation with Henry's constant (r=0.71). Finally, soil half-life had a strong positive correlation with Henry's constant (r=0.77).

The Principal Component Analysis (PCA) for chemical characteristics of the pesticides (Figure 4-2) revealed that cis-permethrin, trans-permethrin, and bifenthrin are most similar to each other in their chemical characteristics and that they are most strongly driven by molecular weight, log K_{ow}, and log K_{oc} , and these characteristics are are opposed by aqueous solubility, and to lesser extent, vapor pressure. Carbaryl and pronamide are most similar to each other in their chemical characteristics and, they are influenced by the same characteristics as permethrin and bifenthrin, but with an opposite effect. The chemical characteristics of trifluralin are not like that of any of the other pesticides. Trifluralin is most directly and strongly influenced by Henry's Law Constant, $K_{air/soil}$, and soil half-life. Based on the PCA, none of the chemical characteristics were compelling for endosulfan.

In assessing the associations between chemical characteristics and detection frequency in yard soil, outdoor air, and house dust (Table 4-4), the strongest association was the positive correlation between vapor pressure and detection frequency in soil (r=-0.88). Although not significant, vapor pressure was also moderately and negatively correlated with indoor dust (r=-0.58). All three media had moderate to very strong negative correlations with aqueous solubility, while all three media also had moderate to very strong positive correlations with log K_{ow} and log K_{oc}. Additional notable negative correlations were found between $K_{air/soil}$ and yard soil (r=-0.76) and house dust (r=-0.58), although these associations were not seen for the outdoor air. Soil half-life was additionally found to have a strong positive correlation with outdoor air (r=0.65), but this was not found for yard soil and house dust.

Table 4-2: Chemical Characteristics of Pesticides of Interest (n=6)

Pesticide	**Molecular Weight (g/mol)** [b,c,d]	**Soil Half-Life (days)**[a,c,f]	**Henry's Constant at 25°C (Pa·m³/mol)**[a,c]	**Aqueous Solubility at 25°C (g/m³)**[a,d]	**Vapor Pressure at 25°C (Pa)** [a,d,e]	**log K_{ow}** [b,c,d]	**log K_{oc}**	**$K_{air/soil}$**
Bifenthrin	422.90	125	$7.40x10^{2}$	0.10	$1.80x10^{-7}$	6.00	4.83	$1.53x10^{-4}$
Carbaryl	201.22	23	$2.80x10^{-4}$	98.63	$1.55x10^{-4}$	1.70	1.42	$1.97x10^{-4}$
Endosulfan	406.95	30	$1.60\ x10^{1}$	0.37	$1.00x10^{-3}$	4.67	3.78	$4.24x10^{-1}$
Permethrin	391.30	32	$4.00x10^{-2}$	0.13	$3.40x10^{-6}$	5.55	4.47	$8.94x10^{-3}$
Pronamide	256.13	40	$6.70x10^{-1}$	15.00	$5.40x10^{-2}$	3.19	2.60	$2.57x10^{-1}$
Trifluralin	355.50	229	$9.60x10^{1}$	0.32	$1.50x10^{-2}$	5.34	4.31	2.2310^{1}

[a]ATSDR, 2003; [b]Krieger and Kriege, 2001; [c]MacKay et al., 1997; [d]MacKay et al., 2007; [e]Hayes and Lewis, 1991, [f]WHO, 2011

Table 4-3: Spearman's Correlations Between Chemical Characteristics of Interest (n=6)

Chemical Characteristics	*Molecular Weight*	*Soil Half-Life*	*Henry's Constant*	*Aqueous Solubility*	*Vapor Pressure*	*log K_{ow}*	*log K_{oc}*	*$K_{air/soil}$*
$K_{air/soil}$	-0.14	0.26	0.14	0.20	0.60	-0.20	-0.20	--
log K_{oc}	0.83*	0.60	-0.66	-1.00	-0.26	1.00	--	
log K_{ow}	0.83*	0.60	0.66	-1.00	-0.26	--		
Vapor Pressure	-0.14	0.49	0.43	0.26	--			
Aqueous Solubility	-0.83*	-0.60	-0.66	--				
Henry's Constant	0.71	0.77	--					
Soil Half-life	0.31	--						

*p<0.05

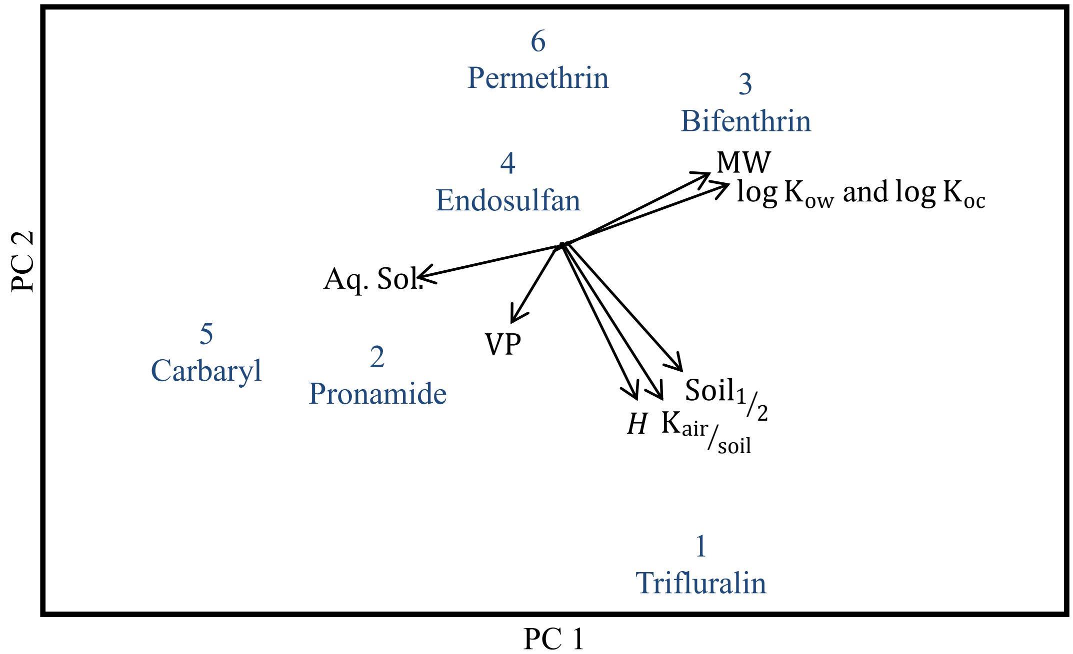


Figure 4-2: Principal Components Analysis for Chemical Characteristics of Pesticides

Table 4-4: Spearman's Correlations Between Chemical Characteristics and Detection Frequency of all Pesticides in Each Media (n=6)

Chemical Characteristic	**Spearman's Rho**		
	Soil	*Dust*	*Outdoor Air*
Molecular Weight	0.27	0.21	0.58
Soil Half-life	-0.15	0.22	0.75
Henry's Constant	-0.21	-0.03	0.72
Aqueous Solubility	-0.52	-0.64	-0.81*
Vapor Pressure	-0.88*	-0.58	-0.03
log K_{ow}	0.52	0.64	0.81*
log K_{oc}	0.52	0.64	0.81*
$K_{air/soil}$	-0.76	-0.58	0.20

*p<0.05

4.3.2 Microclimate/Weather Conditions During Sampling

Sampling of the farmworker's homes was performed over a period of four separate trips. A summary of the microclimate/weather conditions during each sampling trip can be seen in Table 4-5. In general, the average wind speed was higher during the first two sampling trips, which both took place in April 2011 (7.68 mph) compared to the sampling trips in October 2011 (3.84 mph) and February 2012 (5.00 mph). Humidity, on average, was highest during the first April 2011 sampling trip (46%) and lowest in the second April 2011 sampling trip (13%). During the sampling trips in October 2011 and February 2012, humidity was, on average, 25% and 27%, respectively. The only rainfall that occurred was during the first sampling trip in April 2011, in which there was 0.12 inches of rainfall during the second day of the sampling trip. Finally, the average temperature was highest during the October 2012 sampling trip (83°F), followed by the second April 2011 sampling trip (77°F). The sampling trip in February 2012 and the first sampling trip in April 2011 were cooler with an average temperature of 68°F and 60°F, respectively.

Total inches of rainfall and average wind speed were strongly correlated (r=0.71), and this finding was statistically significant (Table 4-6). According to the PCA, rain fall (inches) and humidity (%) had a similar influence (Figure 4-3), although these two conditions were only moderately correlated with each other (Table 4-5). No obvious clustering of homes was observed based on the microclimate/weather conditions (Figure 4-3).

For bifenthrin, rainfall and wind speed were negatively and statistically significantly correlated with outdoor air levels (r=-0.44 for rainfall and r=-0.48 for wind speed) and positively correlated with temperature (r=0.42) (Table 4-7). For trifluralin in the outdoor air, there was a strong statistically significant positive correlation with the average wind speed (r=0.61) (Table 4-7).

Table 4-5: Summary of Weather Conditions During Each Sampling Trip (n=4) (NWS, 2014)

Sampling Start Date	**Day 1 Average**				**Day 2 Average**				**48-Hour Sampling Period Average**			
	Wind (mph)	Humidity (%)	Rain (in.)	Temp (°F)	Wind (mph)	Humidity (%)	Rain (in.)	Temp (°F)	Wind (mph)	Humidity (%)	Rain (in.)	Temp (°F)
4/7/11	8.67	34.04	0.00	72.33	8.03	44.17	0.00	59.28	8.35	39.10	0.00	65.81
4/7/11	8.67	34.04	0.00	72.33	8.03	44.17	0.00	59.28	8.35	39.10	0.00	65.81
4/8/11	8.03	44.17	0.00	59.28	7.03	55.71	0.12	54.33	7.53	49.94	0.06	56.81
4/8/11	8.03	44.17	0.00	59.28	7.03	55.71	0.12	54.33	7.53	49.94	0.06	56.81
4/8/11	8.03	44.17	0.00	59.28	7.03	55.71	0.12	54.33	7.53	49.94	0.06	56.81
4/8/11	8.03	44.17	0.00	59.28	7.03	55.71	0.12	54.33	7.53	49.94	0.06	56.81
4/15/11	7.67	12.46	0.00	73.57	7.21	13.25	0.00	80.30	7.44	12.85	0.00	76.94
4/15/11	7.67	12.46	0.00	73.57	7.21	13.25	0.00	80.30	7.44	12.85	0.00	76.94
4/15/11	7.67	12.46	0.00	73.57	7.21	13.25	0.00	80.30	7.44	12.85	0.00	76.94
10/22/11	3.75	32.25	0.00	82.66	3.94	16.83	0.00	84.18	3.84	24.54	0.00	83.42
10/22/11	3.75	32.25	0.00	82.66	3.94	16.83	0.00	84.18	3.84	24.54	0.00	83.42
10/22/11	3.75	32.25	0.00	82.66	3.94	16.83	0.00	84.18	3.84	24.54	0.00	83.42
2/22/12	5.03	23.00	0.00	64.09	3.90	37.79	0.00	65.23	4.47	30.40	0.00	64.66
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/23/12	3.90	37.79	0.00	65.23	7.35	19.46	0.00	70.57	5.63	28.63	0.00	67.90
2/24/12	7.35	19.46	0.00	70.57	2.85	20.92	0.00	65.13	5.10	20.19	0.00	67.85
2/24/12	7.35	19.46	0.00	70.57	2.85	20.92	0.00	65.13	5.10	20.19	0.00	67.85

*$p<0.05$

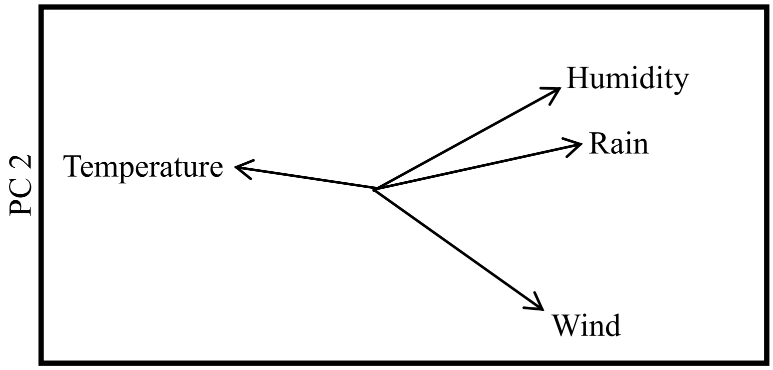


Figure 4-3: Principal Components Analysis of Weather Conditions During Sampling

Table 4-6: Spearman's Correlations Between Weather Conditions During Sampling

Weather Conditions	*Wind Speed*	*Temperature*	*Rain*
Temperature	-0.41	--	
Rain	0.71*	-0.41	--
Humidity	0.04	-0.51	0.41

*p<0.05

Table 4-7: Spearman's Correlations Between Weather Conditions During Sampling Periods and Concentrations of Pesticides in Media (n=4)

Pesticide	**Media**[#]	*Wind Speed*	*Humidity*	*Rain*	*Temperature*
Bifenthrin	*Air*	-0.48*	-0.41	-0.44*	0.42
	Dust	0.24	-0.03	-0.04	-0.05
	Soil	-0.33	0.08	-0.04	-0.15
Permethrin[‡]	*Air*	-	-	-	-
	Dust	0.15	-0.14	-0.08	-0.20
	Soil	-0.24	-0.20	-0.20	-0.02
Trifluralin	*Air*	0.61*	0.36	0.28	-0.35
	Dust	-	-	-	-
	Soil	-	-	-	-

[#] weather conditions averaged over 48-hours for outdoor air; * p<0.05;
[‡]cis and trans isomers combined

4.3.3 Spatial and Temporal Assessment of Pesticide Applications

Spatial and temporal relationships were assessed for bifenthrin, permethrin, and trifluralin. A summary of the pounds of agricultural pesticides applied throughout Yuma County one-month and one-year prior to each sampling trip can be seen in Table 4-8. None of the Spearman's correlations between pesticide pounds applied throughout Yuma County one-month or one-year prior to sampling and pesticide concentrations were statistically significant (Table 4-8).

See Table 4-8 for a summary of pesticide pounds applied during the time periods of one-month and one-year prior to sampling, and within one-mile and a half-mile buffer of the homes sampled. A statistically significant positive correlation was seen between concentration of bifenthrin in outdoor air and pounds of bifenthrin applied within one-month prior to sampling and one-mile of the homes (r=0.62) (Table 4-9). The same trend was seen for between bifenthrin in outdoor air and pounds applied within one-month of sampling and a half-mile of the homes, although this was not statistically significant (r=0.35). A positive correlation was found between the concentration in the house dust and bifenthrin applied within one-year of sampling and one-mile of the homes (r=0.37), but this association was not statistically significant. There was also a significant negative correlation between concentration of trifluralin outdoor air and its application within one-year of sampling and one-mile of the homes (r=-0.44). There were no notable correlations between yard soil or household dust concentrations and agricultural applications.

Table 4-8: Pounds of Agricultural Pesticide Applied Throughout Yuma County Within One-Month and One-Year Prior to Sampling and Spearman's Correlations with Pesticide Concentrations in Outdoor Air, Yard Soil, and House Dust (AZDA, 2014)

Pesticide	Time Prior	Trip #	Homes Sampled	Dates	Pounds Applied	Spearman's Rho		
						Air	*Soil*	*Dust*
Bifenthrin	Month	1	6	March 7-April 9, 2011	761.25	-0.04	-0.06	-0.35
		2	3	March 15-April 17, 2011	726.50			
		3	3	September 22-October 24, 2011	4,819.15			
		4	9	January 22-February 24, 2012	773.44			
	Year	1	6	April 7, 2010-April 9, 2011	44,547.23	-0.29	0.12	0.18
		2	3	April 15, 2010-April 17, 2011	44,520.64			
		3	3	October 22, 2010-October 24,2011	23,938.76			
		4	9	February 22, 2011- February 24, 2012	20,672.20			
Permethrin	Month	1	6	March 7-April 9, 2011	58,16.90	-0.26	0.28	0.23
		2	3	March 15-April 17, 2011	78,18.64			
		3	3	September 22-October 24, 2011	13,152.53			
		4	9	January 22-February 24, 2012	85,50.31			
	Year	1	6	April 7, 2010-April 9, 2011	76,77.63	-0.05	0.27	0.17
		2	3	April 15, 2010-April 17, 2011	27,96.80			
		3	3	October 22, 2010-October 24, 2011	30,437.44			
		4	9	February 22, 2011- February 24, 2012	61,281.45			
Trifluralin	Month	1	6	March 7-April 9, 2011	57,589.49	0.02	.	.
		2	3	March 15-April 17, 2011	38,138.74			
		3	3	September 22-October 24, 2011	1,456.81			
		4	9	January 22-February 24, 2012	11,478.00			
	Year	1	6	April 7, 2010-April 9, 2011	189,257.28	0.07	.	.
		2	3	April 15,2010-April 17, 2011	183,525.28			
		3	3	October 22, 2010-October 24, 2011	166,249.94			
		4	9	February 22, 2011- February 24, 2012	115,435.28			

Table 4-9: Pounds per Square Mile of Agricultural Pesticide Applied in Buffers Around Each Home One-Month and One-Year Prior to Sampling and Spearman's Correlations with Pesticide Concentrations in Yard Soil, Outdoor Air, and House Dust (n=19)

Pesticide	Time Period	Buffer (mile)	Min	25th %	50th %	75th %	Max	Spearman's Rho *Soil*	Spearman's Rho *Air*	Spearman's Rho *Dust*
Bifenthrin	Year	1	0.00	33.00	46.77	79.25	133.87	0.07	-0.27	0.37
		0.5	0.00	1.92	46.56	62.75	70.30	-0.18	0.09	0.02
	Month	1	0.00	0.00	0.00	0.31	23.75	0.28	0.62*	-0.21
		0.5	0.00	0.00	0.00	0.00	63.35	0.18	0.35	-0.21
Permethrin‡	Year	1	0.00	13.32	28.63	44.59	72.52	0.00	--	-0.10
		0.5	0.00	0.01	14.90	30.67	50.74	0.02	--	-0.17
	Month	1	0.00	2.67	5.60	20.62	24.60	0.03	--	-0.15
		0.5	0.00	0.12	8.00	20.49	24.15	0.06	--	-0.23
Trifluralin	Year	1	0.00	0.38	65.86	142.85	247.94	--	-0.44*	--
		0.5	0.00	0.00	0.00	6.54	324.33	--	-0.04	--
	Month	1	0.00	0.00	0.00	0.00	133.58	--	0.09	--
		0.5	0.00	0.00	0.00	0.00	0.00	--	.	--

*p<0.05; -- DF < 25% for media; . no pesticides applied in during time period and spatial buffer

4.4 Discussion

4.4.1 The Importance of Considering External Risk Factors in Association with Agricultural Pesticide Levels in Farmworkers' Homes

A major uniqueness of the current study was the exploration of a variety of external risk factors, defined to be factors that are not directly related to that of the farmworkers or their household, and the assessment of whether these factors were associated with the agricultural pesticides detected at farmworkers' homes. Previous studies have demonstrated that chemicals in the environment can be influenced by factors such as chemical characteristics, microclimate/local weather conditions, and the spatial and temporal distribution of the chemical's application in the environment (Akesson and Yates, 1964; Bache and Johnstone, 1992; Wauchope et al., 1992; Gunier et al., 2001; Ares et al., 2006; MacKay et al., 2006; Posen et al., 2006; Levine, 2007; Luo et al., 2010; USEPA, 2014b). However, studies that assess the association between these types of factors and the results of sampling studies have very limited.

4.4.2 The Influence of Chemical Characteristics

It was found that chemical characteristics can be useful for understanding why certain agricultural pesticides were detected more frequently than others in each type of media, especially when a certain chemical characteristic was particularly notable for a pesticide or a group of pesticides. For example, in the current study, carbaryl and pronamide both had 0% - 5% detection frequency (DF) in all three media sampled. According to the PCA for the chemical characteristics of pesticides, carbaryl and pronamide cluster together, suggesting similarity, and both appear to be driven strongly by their aqueous solubility. This is as expected since these two pesticides have the highest solubility values of all the pesticides assessed. Since aqueous solubility expresses how readily a chemical dissolves in water, it is expected that pesticides with high aqueous solubility would have low sorption to particles, and therefore a have high potential for leaching into groundwater or run-off surface water. This notion is supported by the positive correlation between log K_{ow} and the detection frequency in the soil (r=0.52) and house dust (r=0.64), and the negative correlation between aqueous solubility and detection frequency in the soil (r=-0.52) and house dust (r=-0.64). Therefore, pesticides with a higher solubility are less likely to be detected in soil and house dust. Although carbaryl and pronamide were not well detected in the current pesticide sampling, if ground/surface water had been included as sampling media, it is predictable that these pesticides would have been detectable in those media.

Endosulfan also had a very low detection frequency in this study, but it is unlikely that the chemical characteristics of this pesticide are the driving force behind the lack of detection in the environmental samples. This pesticide does not have any striking chemical characteristics; rather, each of endosulfan’s chemical characteristics was near the geometric mean of that characteristic for all of the pesticides combined. Therefore, endosulfan appears to be a “middle of the road” pesticide without any strong chemical characteristics driving its detection in the environment.

Another reason why endosulfan, pronamide, and carbaryl, were all not readily detected in the environmental media may be related to laboratory analysis capabilities. Endosulfan, pronamide, and carbaryl all shared the highest minimum detection limit (MDL) compared to the rest of the pesticides in the analysis suite for all three media. This may suggest that with enhanced laboratory analysis capabilities, these pesticides would have had a higher detection frequency.

Detection frequency of trifluralin, which was very high in the outdoor air (DF 95%), but very low in the soil (DF 0%) and house dust (DF 5%), may be partially explained by trifluralin's chemical characteristics. Trifluralin's vapor pressure of $1.5x10^{-2}$ Pa is within the range that has been shown to be more favorably in the vapor phase (Bidleman, 1998). The lack of detection of trifluralin in either the soil or the house dust can be explained by the finding that vapor pressure has a strong negative correlation with detection frequency in outdoor soil (r=-0.88) and a moderate negative correlation with detection frequency in house dust (r=-0.58), suggesting that pesticides with a high vapor pressure, which preferentially partition into the vapor phase, are less likely to be detected in soil and house dust. Similarly, $K_{air/soil}$, which expresses the partitioning between the vapor phase in the air and soil particles, was negatively correlated with soil detection frequency (r=-0.76) and dust detection frequency (r=-0.58), which were expected findings given that $K_{air/soil}$ can be calculated using vapor pressure. For trifluralin in particular, the $K_{air/soil}$ was up to three orders of magnitude higher than the other pesticides of interest in our study, further suggesting that the detection frequency in the air was primarily in the vapor phase in the outdoor air.

Permethrin and bifenthrin were both detected in all three media, and since they are both insecticides of the pyrethroid family, they resultantly clustered together in the PCA for chemical characteristics. For bifenthrin, detection frequency was very similar for all three media sampled, although it was a bit higher in house dust (DF 48%) compared to the outdoor air (DF 43%) and soil (DF 38%). For permethrin, the detection frequency was much higher in the house dust (DF 91%) and soil (DF 96%), compared to the outdoor air (19%). The low vapor pressures of bifenthrin ($1.8x10^{-7}$ Pa) and permethrin ($3.4x10^{-6}$ Pa) were a highly influential chemical characteristic for these two pesticides. Given that it has been previously shown that chemicals with a vapor pressures less than $1x10^{-5}$ Pa are largely in the particle-phase (Bidleman, 1998), it is likely that bifenthrin and permethrin adhere to soil particles, and therefore, detection in the outdoor air of these pesticides was a result of resuspended contaminated soil particles. In addition, the two highest octanol-water partition coefficients (log K_{ow}) of any of the pesticides in this study were bifenthrin (log K_{ow} =6.0) and permethrin (log K_{ow} =5.5). This suggests strong partitioning into an octanol substance rather than water, given that a log K_{ow} of >3 is widely considered to indicate strong hydrophobicity. Since log K_{ow} and log K_{oc} are perfectly correlated with each other (r=1.00), it can be reasoned that bifenthrin and permethrin's strong hydrophobicity also indicates that they have strong adherence to soil. Bifenthrin and permethrin also have the two lowest aqueous solubilities of the pesticides in our study, and in previous laboratory studies, soil leaching was reported to be minimal for both pesticides (Ismail and Kalithasan, 2004; Manoj and Gajbhiye, 2007). The moderate positive correlations between log K_{ow} /log K_{oc} and the detection frequency in the soil (r=0.52) and house dust (r=0.64), along with the negative correlation between aqueous solubility and detection frequency in soil (r=-0.52) and house dust (r=-0.64) support the idea that permethrin and bifenthrin are well adhered to particles. It should be noted that all of the chemical characteristics that suggest a preference for particles were more pronounced for bifenthrin compared to permethrin (e.g., longer soil half-life, lower vapor pressure, higher log K_{ow}, higher log K_{oc}, and lower $K_{air/soil}$), and therefore particle adherence should be stronger for bifenthrin compared to permethrin.

4.4.3 The Influence of Microclimate/Weather Conditions During Sampling

Examining the microclimate/weather conditions during the time of sampling helped to explain pesticide concentrations in the outdoor air, although consideration of these conditions was not as effective for explaining soil and house dust levels. This was expected because the outdoor air was collected over a period of 48-hours, thereby subjecting the air sample collection to the weather, which varied by to 40 degrees throughout the duration of the sampling period (NWS, 2014). On the other hand, both soil and house dust samples were collected at a single time point, which would not be affected by the varying weather conditions over a period of time.

Wind speed, humidity, and rainfall all influenced the outdoor air levels in the same direction for each pesticide (i.e., negatively correlated with bifenthrin and positively correlated with trifluralin), while temperature influenced the levels in the opposite direction (i.e., positively correlated for bifenthrin and negatively correlated for trifluralin). The PCA for weather conditions during household visits also suggested similar results because humidity, rainfall, and wind speed were all clustered in the opposite direction of temperature.

In this study, moderate correlations were observed between the average temperature during sampling and the outdoor air levels of trifluralin (r=-0.35) and bifenthrin (r=0.42). A prior study that measured trifluralin in the air for 13 days post-application found that volatilization patterns changed with temperature throughout the day, but this effect was posited to actually be driven by changes in soil moisture that occur with changes of temperature (Bedos et al., 2006). In that study, volatilization increased throughout the morning hours, coinciding with increasing soil surface temperature, but then volatilization decreased as temperatures continued to increase throughout the day. Volatilization sometimes increased again in the evening as temperatures began to cool. It was concluded that the lower concentration of trifluralin in the outdoor air, which corresponded to a higher average temperature, may be a result of hindered volatilization that occurs with higher temperature. Likewise, an older study also reported pesticide volatilization to be strongly driven by increased soil moisture (Taylor and Spencer, 1990).

It is also well established that volatilization rates increase with wind speed (CEPA, 1995). This helps to explain the significant positive correlation between trifluralin in the outdoor air and wind speed since, trifluralin is thought to be almost exclusively in the vapor phase. The findings of the current study are also consistent with a previous New Mexico study that measured outdoor air levels of trifluralin, and found that trifluralin concentrations were positively dependent on wind speed and humidity, both of which promote volatilization and soil resuspension (Holmén et al., 2013).

Previous studies have also established a negative relationship between concentrations of particulate matter (PM) with humidity and rainfall (Giri et al., 2007; Mokhtar et al., 2009; Dominick et al., 2012). Given that it is believed that airborne bifenthrin is almost exclusively in the particle phase, the current study's finding that humidity and rain were negatively correlated with the outdoor air levels of bifenthrin was as expected. The current study's additional finding that average temperature was positively correlated with outdoor air concentrations of bifenthrin (r=0.42.) may be explained by the fact the formation of wind is a direct result of an increased temperature differential (Wooten, 2011). As such, increasing temperatures are likely to drive particles into the air via the wind. In addition, higher temperatures increase the drying of soil surfaces, which would increase soil absorption, promoting resuspension of particles into the air. It is well-established that the community of interest for this study, Yuma County, Arizona, has an unusually hot and dry climate compared to many other parts of the United States, further suggesting a that a lack of soil moisture and high temperatures may have play a role in resuspending bifenthrin into the outdoor air. Unfortunately, associations between weather conditions and airborne permethrin could not be assessed due to the low detection frequency in the outdoor air.

Results from previous studies suggest that the relationship between wind speed and particulate matter (PM) concentration can vary (Giri et al., 2007; Mokhtar et al., 2009; Dominick et al., 2012). One study in Nepal found positive and statistically significant correlations between PM concentration and wind speed during the pre-monsoon (March-May) and monsoon seasons (June-September), yet negative, though insignificant, correlations between PM concentrations and wind speed during the post-monsoon (October-November) and winter seasons (December-February) (Giri et al., 2007). Given that all of the sampling in the present study was done outside of monsoon season months, and the majority was done outside of pre-monsoon season months, the findings are of the current study for bifenthrin consistent with those of Giri et al. (2007). One limitation of the current study is that that there was a lack of information on wind direction in relation to agricultural fields where the pesticides of interest were applied. In the previously described study by Giri et al. (2007), the researchers reported that wind direction had no effect on PM concentration. However, future pesticide sampling studies may still consider exploring wind direction with a more in depth assessment of which pesticides are applied in each direction from the home.

It is possible that the level of particles may have been underestimated in the current study's outdoor air samples given that the PUF/XAD-2/PUF sampler has been shown to be more effective for capturing pesticides in the vapor phase compared to the particle phase. In the future, it may be useful to additionally use a glass fiber filter or quartz fiber filter in line with the PUF/XAD-2/PUF to better capture particles, as has been done in previous studies (Chuang et al., 1987; Odabasi et al., 1999; Wania et al., 2003). Additionally, XAD-2 resin is known to retain small particles, which may not be efficiently removed by solvent extraction (Grasshoff et al., 1999), which was extraction technique used in the current study.

4.4.4 The Influence of Spatial and Temporal Applications of Pesticides

Exploration of the relationships between the agricultural applications of pesticides within the different spatial and temporal buffers and the pesticides detected at the farmworkers' homes were found to be the most notable for pesticide detection in the outdoor air. Also, based on the strength of the resulting correlations, different buffers were found to be better predictors for the different pesticides. The one-mile spatial buffer was consistently a better predictor to examine the association between agricultural pesticide applications and pesticide levels at farmworkers' homes, compared to the half-mile buffer. However, in some cases, consideration of all agricultural pesticide applications throughout Yuma County, Arizona was a better predictor than the one-mile spatial buffer. The optimal temporal buffer also varied, but the one-month prior buffer was usually the better predictor for bifenthrin and permethrin, while the one-year prior buffer was a better predictor for trifluralin.

Bifenthrin concentrations measured at the farmworkers' homes showed almost no relationship with bifenthrin agricultural applications throughout Yuma County, with the exception of a moderate correlation between bifenthrin in the house dust and applications within one-month prior to sampling in Yuma County. This correlation was negative ($r=-0.35$), and although it was not statistically significant, this could suggest that the farmworkers' homes were not highly impacted by the pesticide applications throughout the entire County, but rather by pesticide applications near the home. This notion is supported by the additional finding that agricultural applications of bifenthrin applied within one-year prior to sampling and one-mile of the home, there was a moderate positive correlation with the house dust ($r=0.37$).

Likewise, bifenthrin concentrations in the outdoor air were strongly correlated with agricultural applications within one-month of sampling for a one-mile buffer (r=0.62), and this finding was statistically significant, once again suggesting nearby agricultural applications of bifenthrin may be a concern for farmworkers' families. The same trend was found for bifenthrin in the outdoor air within the half-mile buffer (r=0.35), although this finding was not significant. Notably, correlations with outdoor soil for both the temporal or spatial buffers were much weaker, although still positive for both the one-mile (r=0.28) and half-mile (r=0.18) buffers, suggesting that agricultural pesticides such as bifenthrin are transported into the community primarily through the air rather than through the soil.

Like bifenthrin, permethrin concentrations measured at the farmworkers' homes showed weak relationships with permethrin applied agriculturally throughout Yuma County, although it was interesting to find that the correlations were positive for the outdoor soil and house dust, while negative for the outdoor air for both one-month and one-year prior to sampling. Unlike bifenthrin, there were even weaker associations between the level of permethrin detected at the farmworkers' homes and agricultural applications of permethrin near to the farmworkers' homes within the one-mile and half-mile buffers. Only soil and dust could be assessed for permethrin because the detection frequency in the outdoor air was too low (DF 19%). One reason why the associations with the soil and house dust were so weak could be the fact that permethrin has a relatively short soil half-life (~28 days) (IPCS, 1990). With the temporal buffers set to one-month and one-year, it would be more difficult to detect a pesticide with a soil half-life of less than one month and therefore, taking into account applications throughout the entire County may have helped to reveal the relationship between agricultural applications and permethrin levels detected at the farmworkers' homes. As expected, correlations between permethrin levels in the sampled environmental media and the agricultural pesticide applications of permethrin within one-month prior to sampling were a bit stronger than within one-year prior to sampling, but this difference was much less drastic than expected. Another possible reason why the associations between permethrin agricultural applications and detections in the soil and house dust were so weak could be due to alternative sources of permethrin, such as use of residential products containing permethrin or household materials, such as furniture, treated with permethrin.

Although trifluralin could only be assessed in the outdoor air, it was interesting that concentrations in the current study were, in fact, negatively correlated with the amount of trifluralin pesticide applications within one-year and one-mile of the sampled homes (r=-0.44). On the other hand, there was no correlation within one-year and a half-mile from the sampled homes (r=-0.04) or within one-month and one-mile (r=0.09). Note that no known pesticides were applied within one-month and a half-mile, so no correlation was run for this spatial and temporal buffer. The fact that airborne trifluralin concentrations do not follow the normally expected pattern with distance from application is a finding that has been observed previously in the peer-reviewed literature (Majewski et al., 1998; Holmén, 2013). In one study that measured airborne trifluralin along the Mississippi River, the areas of highest trifluralin application did not coincide with the highest trifluralin concentration in the air (Majewski et al., 1998). Additionally, the previously mentioned study in New

Mexico reported no direct relationship between the airborne concentrations and distance from the tractor that applied trifluralin (Holmén, 2013). Results of the current study lend further support to the idea that distance from application may not be very useful in predicting airborne concentrations in trifluralin. The negative correlation between airborne trifluralin with the amount of its agricultural pesticide applications within one-year and one-mile of the sampled homes (r=-0.44) suggests that trifluralin has a high potential to drift through the air, and that perhaps areas further away from initial application could be most impacted. This suggestion is consistent with the findings of a previous study that detected vapor-phase trifluralin in a rural community north of Toronto, to which the authors suggested was a result of long-range transport from an area in western Canada where the pesticide was heavily used (Hoff et al., 1992).

Comparison of the associations with agricultural pesticide applications throughout all of Yuma County to those limited to within the one-mile and half-mile buffers, along with the one-month and one-year prior to sampling buffers, highlights the importance of assessing more than one buffer (i.e., one-mile versus half-mile versus all of Yuma County; one-month versus one-year) for spatial and temporal trends. The results of the current study showed that different spatial buffers and temporal buffers were more effective for understanding the relationships with pesticide levels in the environment depending on both the specific pesticide of interest and the environmental media of interest. Limiting all spatial and temporal assessments to one generic buffer could tell the wrong story and underestimate or overestimate the strength of the relationship with pesticide levels at the home, thereby making incorrect insinuations about the potential exposure risk to farmworkers' families. In general, the spatial and temporal distribution of pesticide application may be more relevant for airborne pesticides predominantly in the particle phase compared to those largely in the vapor phase.

One major limitation of the spatial and temporal assessments was the fact that the details regarding the method of pesticide application in the agricultural fields (e.g., aerial, ground sprayer) could not be ascertained from the Arizona Department of Agricultural Pesticide Use "1080" Database (see Figure 4-1 for details on the information available through the Database). The issue of pesticide spray drift upon agricultural pesticide application has been well-established for many years in the peer-reviewed literature, and variations in drift have been shown to depend on the type of pesticide spray equipment used (e.g., aircrafts, ground sprayers) and the design of that equipment (e.g., types of nozzles, type of aircraft) (Frost and Ware, 1969; Ware et al., 1969; Stewart and Gratkowski, 1976; Smith et al., 1981, Salyani and Cromwell, 1992). For example, Frost and Ware (1969) reported that drifting of pesticide residues up to a half-mile downwind from the pesticide application were 80% higher for aerial applications compared to the use of a high clearance ground sprayer. Göhlich (1983) found that using an air-blower ground sprayer resulted in greater drift compared to using a spray gun or a helicopter, while in Salyani and Cromwell (1992), no major differences in pesticide spray drift were found between aerial and ground spraying. Bode and Zain (1987), Bird et al. (1999), and Salyani and Cromwell (1992) all reported greater drift from low-volume applicators compared to conventional nozzles that release at a higher volume. More recently, research related to drift retardants has been explored, and a wide range of effectiveness of these products has been reported. (VanGessel and Johnson, 2005; Wolf et al., 2005; Guler et al., 2006). For example, Wolf et al. (2005) reported that some spray drift retardants added to the solution containing the pesticide prior to fixed-wing aerial applications reduced drift compared to the drift of water, while others products increased the drift or performed the same as water.

It would have been very insightful to assess the difference in pesticide detection based on the spatial and temporal trends of agricultural pesticides applications by type of pesticide spray equipment used, along with the design of that equipment and whether any drift retardants were utilized. Although this information was not available from the Arizona Department of Agricultural Pesticide Use “1080” Database, there could be potential for future researchers to work directly with the Arizona Department of Agricultural Pesticide Use and possibly ascertain this information in an alternative way.

4.4.5 Conclusions

This study has positively contributed to the improved identification and characterization of external risk factors by assessing the association between the results of the pesticide sampling in the farmworkers’ homes with the inherent chemical characteristics of pesticides applied in the agricultural community, microclimate/weather conditions during the sampling period, and the spatial and temporal distributions of pesticide applications, which successfully fulfills the second aim of this dissertation. Multiple inherent chemical characteristics of the pesticides were found to influence how pesticides were transported away from agricultural fields to the homes of farmworkers. The microclimate/weather conditions during the time of sampling, along with the spatial and temporal distributions of the agricultural pesticide applications, were most strongly associated with pesticide concentrations in the outdoor air at the farmworkers' homes. These findings confirm the hypotheses posited for the second aim of this dissertation. The relevance of pesticide transport from agricultural fields to homes through the outdoor air, and subsequently into homes via air infiltration, is strongly suggested by the results of the current study, and it is recommended that future interventions to reduce pesticide levels in farmworkers' homes focus on factors related to transport through the air.

CHAPTER 5

IDENTIFYING HOUSEHOLD-LEVEL RISK FACTORS THAT INFLUENCE AGRICULTURAL PESTICIDE LEVELS AT FARMWORKERS' HOMES

5.1 Introduction

It is well established that agricultural pesticides can often be detected in the homes of farmworkers, most notably in the house dust (Lu et al., 2000; McCauley et al., 2001; Whyatt et al., 2002; Colt et al., 2004; Bradman et al., 2005; Bradman et al., 2006; Robert et al., 2009). Additionally, it is known that people spend the majority of their time indoors (Farrow et al., 1997) making at-home exposure to pesticides a pressing environmental health issue for farmworkers and their families (Thompson et al., 2003; Quandt et al., 2004; Arcury et al., 2005; Coronado et al., 2006; Arcury et al., 2007).

Despite the strong evidence that pesticide transport occurs from agricultural fields into farmworkers' homes, there is a lack of federal regulation in the United States to protect families against such exposure (Goldman et al., 2009). None of the current environmental legislation designed to protect the public from pesticide exposure, including the Clean Water Act, the Safe Drinking Water Act, the Federal Insecticide, Fungicide, and Rodenticide (FIFRA), and the Food Quality Protection Act of 1996 (FQPA 1996) involve regulation of agricultural pesticides levels in the soil, air, or house dust at residences surrounding an agricultural field (PMEP, 1993, USEPA, 2015c; USEPA, 2015d). Although under FQPA 1996, the federal government is required to perform risk assessments that take into account aggregate pesticide exposures from all sources and cumulative exposures of multiple pesticides with the same mechanism of toxicity (ibid), the risk assessment exposure scenarios do not include residential exposure to agricultural pesticides.

With the onus to prevent pesticide transport into farmworkers' homes currently falling mostly on the farmworkers and their household, it is important to explore whether such families may be able to proactively prevent pesticide transport into their homes. As a result, environmental health and public health researchers have begun to realize the need to explore household-level risk factors that could influence the transport of agricultural pesticide into homes.

Studies in the peer-reviewed literature report that farmworkers may engage in behaviors that promote take-home/soil track-in of pesticides into the home, such as wearing work shoes in the home or neglecting to shower after work, often referring to this as the "take-home" pathway (Arcury et al., 1999; McCauley et al., 2001; Thompson et al., 2003; Goldman et al., 2004; Cabrera and Leckie, 2009). In response to these findings, previous interventions mostly targeted the take-home/soil track-in pathway with the strategy of empowering farmworkers to change their own behaviors related to this pathway (Thompson et al., 2008; Arcury et al., 2009; Salvatore et al., 2009; Strong et al., 2009). Unfortunately, there has never been a successful reduction of agricultural pesticide levels in the household as a result of any previous intervention study focusing on farmworkers' behaviors related to the take-home/soil track-in pathway (ibid). Therefore, it is necessary to expand the exploration of the household-level factors can influence the transport of agricultural pesticides into the homes of farmworkers.

Among the many previous sampling studies, several did not report basic household-level factors (Rothlein et al., 2006; Curl et al., 2002), or the study described some of these factors, but did not perform statistical analysis to assess the factor's relationship with pesticide levels measured in the home (Thompson et al., 2003; Coronado et al., 2006; Bradman et al., 2007; Bradman et al., 2011; Quirós-Alcalá et al., 2011). A few studies did explore a variety of household-level factors and assessed their association with agricultural pesticides in house dust (Simcox et al., 1995, McCauley et al., 2001, Quandt et al., 2004). Some of the previously reported household-level factors included proximity to an agricultural field or orchard (Simcox et al., 1995; McCauley et al., 2001; Quandt et al., 2004), level of difficulty to clean the house (Quandt et al., 2004), and the number of people living in the home (both in general and specifically employed in agriculture) (McCauley et al., 2001).

The third major aim of this dissertation was to identify relevant household-level risk factors for increased in-home agricultural pesticide levels. Household-level risk factors are defined as those directly related to the farmworkers or their household. In the current Chapter, the author provided an exploratory approach, through a series of univariate analyses, to assess the influence of the various household-level risk factors on increased in-home agricultural pesticide levels.

The analyses of this Chapter partially fulfill the third major aim of this dissertation, and are combined with the analyses of Chapter 6 to fully address this aim and its associated hypotheses.

5.2 Methods

5.2.1 Categories of Potentially Influential Household-Level Risk Factors

Using the questionnaire administered during the sampling stage of this project (described in Chapter 2 of this dissertation), potentially influential household-level risk factors related to agricultural pesticide transport into homes were explored. Each potentially influential factor belonged to one of the following categories: household member characteristics, household behaviors, and housing structure characteristics. Household member characteristics were furthered categorized into: basic demographics, type of household residents, and household pets. Household behaviors were further categorized into: farmworker hygiene/ take-home behaviors, cleaning and maintenance of house, and temperature control and ventilation. Housing structure characteristics were further categorized into: structure size and age, ground and floor coverings, and temperature control and ventilation.

5.2.2 Handling of Pesticide Concentration Data

Pesticide concentration data was attained from the sampling component of this dissertation project (see Chapter 2 for details). The minimum, median, and maximum concentrations of bifenthrin and permethrin in house dust were reported for each potentially influential household-level risk factor. In house dust, the MDL was 14.14 ng/g for bifenthrin and 5.66 ng/g for permethrin. Please note that reported permethrin values are the sum of the *trans*-permethrin and *cis*-permethrin isomers, for which the MDL was 2.83 ng/g for each isomer. Samples that did not have detectable pesticide concentrations were designated non-detectable (ND). In the current study, all ND concentrations were replaced with the minimum detection limit (MDL)/√2, which has previously been shown to be the preferred method for handling data with low to moderate variability when up to half of the samples have non-detectable values (Hornung and Reed, 1990).

5.2.3 Handling of Questionnaire Responses

Questionnaire responses were tabulated (number and percent frequency), and in some cases, categories were created or combined prior to tabulation based on natural breaks in the reporting results as determined through a process of visually examining the distribution of the questionnaire response. When no answer was provided from a household for a specific question, this particular observation was removed from further tabulation and statistical analysis.

Most of the questionnaire responses were categorical variables, and thus Kruskal-Wallis tests were used to assess associations between each response and pesticide concentrations in the house dust. When there was a significant finding from the Kruskal-Wallis test ($p<0.05$), paired Wilcoxon Rank Sum tests were performed to determine where the difference occurred. Additionally, post-hoc Bonferroni corrections were used to account for multiple comparisons, and the results were reported with and without this correction.

A few questionnaire responses were continuous or discrete variables. Square footage of the house was considered a continuous variable, and the number of each type of the following household resident was considered as discrete variables: total people, children, farmworkers, indoor pets, and pets that move in and out of the house. The number of each type of household resident (e.g., total people, children) was additionally adjusted by square footage of the house. This was done by dividing the number of each household resident by the square footage of the house and then handling the calculated values as a new continuous variable. The author decided against subsequently breaking the calculated household residents per square footage into categories because this would be difficult to interpret (i.e., the results could be abstract, such as “0.1 child”). In addition, the results could potentially be misleading because categorical splits of a continuous variable result in a loss of power (Aikin and West, 1991) and in this case, two continuous variables would be compromised. Testing associations of the continuous variable with concentration of bifenthrin and permethrin in house dust was done using Spearman’s rank correlations. Interpretation of Spearman’s r-value is considered highly subjective and variable, so for purposes of the current study, the author decided to interpret the r-values as follows: >0.40-0.59 as a moderate correlation, 0.60-0.79 as a strong correlation, and 0.80-1.00 as a very strong correlation. All Spearman’s rank correlations were also tested for statistical significance at an alpha level of 0.05.

5.2.4 Assessing Distance from Home to Nearest Agricultural Field

Distance from home to nearest agricultural field was assessed independently. During the questionnaire administration, participants reported whether their home was <0.5 mile, 0.5-1 mile, or >-3 miles from the nearest agricultural field. To supplement the self-reported results, GoogleEarth® (Google Inc., 2015) was used to measure the actual distance from the home to the nearest agricultural field. Distances were measured by mapping each participant's address and viewing the nearest agricultural field using the satellite view function. The ruler function was used to measure the distance from the participant's address to the nearest edge of the agricultural field. In a few cases, it was initially unclear whether the area on the map was indeed an agricultural field, so maps from previous dates (an available option in GoogleEarth®) were viewed until it could be visually confirmed that it was indeed an agricultural field.

Spearman's rank correlations were used to assess the association between measured distances from homes to the nearest field as determined in GoogleEarth® (Google Inc., 2015) and the concentrations of bifenthrin and permethrin in house dust. Kruskal-Wallis tests were used to assess whether there were significant differences in the house dust levels for each pesticide based on the three designated distance categories (i.e., <0.5 mile, 0.5-1 mile, >1-3 miles) for both the questionnaire reported distances and the GoogleEarth® measured distances. A second set of Kruskal-Wallis tests was used to assess whether there were differences in the house dust levels based on cut-off points of 200 feet, 400 feet, and 800 feet. A third set of Kruskal-Wallis tests were used to assess differences based on homes <200 feet from a field and ≥200 feet. The incorporation of these latter two sets of cut-off points were chosen to facilitate comparison with the multiple previous agricultural pesticide studies, which assessed distances using similar cut-off points (Simcox et al., 1995; Loewenherz et al., 1997; Fenske et al., 2002; Weppner et al., 2006). Please note that the address for one of the homes could not be determined so distance to a field could not be measured with GoogleEarth® (Google Inc., 2015). As a result, this particular home was removed from all analyses for distance between home and field for both the measured distances and self-report distances. Although this particular home could have been included in the analyses for the self-reported distances, it was removed for the purposes of better comparison with the analyses pertaining to measured distances.

5.2.5 Assessing Residential Pesticide Use

Since bifenthrin and permethrin could potentially have residential uses at low concentrations (Weston et al., 2005), the effect of residential pesticide use was also assessed. For homes that reported that they "don't know" which active ingredients of the residential pesticides were used (either by the family or through professional application), exploratory analysis was performed so the "don't know" responses were handled in four different ways. First, it was assumed that homes that did not know the active ingredients of products applied did indeed use the pesticide of interest. Next, the homes that did not know the active ingredient of their products were excluded all together. Then, responses from homes that did not know the active ingredients of products were placed into a unique "don't know" category. Finally, it was assumed that homes that did not know the active ingredients of products applied did not use the pesticide of interest. Kruskal-Wallis tests were used to see if there were differences in the detected levels of bifenthrin or permethrin using each of the four previously described methods of handling the "don't know" responses.

5.3 Results

Potentially influential factors for (1) household member characteristics, (2) household behaviors, and (3) housing structure characteristics are summarized by tabulation (n) about percent frequency (%). For results of Kruskal-Wallis tests, the p-value is reported to denote whether or not the findings were statistically significant. For results of the Spearman's Rank Correlations, the r-value and p-value are both reported to illustrate the strength of the correlations, along with whether or not the results were significant.

5.3.1 Household Member Characteristics and Pesticide Concentrations

5.3.1.1 Summary of Household Member Characteristics

Overall, the study participants had a relatively low education and income; the majority did not finish high school and just over half had an annual household income of less than $21,000. All but one participant preferred speaking Spanish, rather than English. Over 60% of families had four or less people in the home. The number of children ranged from zero to four, and the number of farmworkers ranged from one to three. Pets largely remained outdoors; only a few families had indoor pets or pets that moved in and out of the house. A summary of household member characteristics can be seen in Table 5-1. In addition, all participants self-identified as Mexican, Hispanic, or Latino and none of the families smoked inside the home (not included in Table 5-1 due to lack of variation in results).

5.3.1.2 Household Member Characteristics and Bifenthrin in House Dust

There were no notable differences for bifenthrin in house dust by basic demographics of participant education (p=0.33), annual income (p=0.65), or preferred language (p=0.37) (Table 5-2). Positive, but weak correlations were observed between bifenthrin in house dust and each type of household resident, namely people (r=0.35, p=0.12), farmworkers (r=0.24, p=0.30), and children (r=0.29, p=0.19) living in the home. Yet, when each group was adjusted for square footage of the home, almost no correlations were observed (Table 5-3). Neither pets that remained indoors (r=-0.12, p=0.59), nor pets that moved in and out of the house (r=0.03, p=0.88), were correlated with bifenthrin in house dust, and this remained the same after adjustments for square footage of the house. Finally, square footage itself was positively correlated with bifenthrin in house dust (r=0.26, p=0.27)) (Table 5-3).

5.3.1.3 Household Member Characteristics and Permethrin in House Dust

Among the basic demographics, it was observed that permethrin in house dust was generally higher in homes in which the participant had completed high school, yet the maximum level was found in a home where the participant had not completed high school (p=0.42) (Table 5-4). No differences in permethrin levels of house dust were seen based on household annual income (p=0.83) or participant preferred language (p=0.51) (Table 5-4). For the type of household residents, the number of children living in the home was found to be moderately and negatively correlated with permethrin in house dust (r=-0.35, p=0.11), but when adjusted for square footage, this correlation became weak. Less notably, but also negatively correlated with permethrin in house dust, were number of people (r=-0.19, p=0.42) and farmworkers (r=-0.14, p=0.54), and square footage adjustments also weakened these correlations. For household pets, permethrin in house dust was weakly correlated with both indoor pets (r=0.18, p=0.44) and pets that move in and out (r=0.02, p=0.94)) before and after square footage adjustments (Table 5-5). Given the strength of the correlation between children and permethrin in the house dust compared to all of the other types of household resident, the difference between the presence or absence of children in the home was additionally tested using a Kruskal-Wallis test, but no significant difference was found when testing the data this way (p=0.21).

Table 5-1: Tabulations and Frequencies of Household Member Characteristics

Household Member *Category*	*Characteristic*	*n (%)*
	Participant education	
	<12 years	17 (81.0)
	≥12 years	4 (19.0)
	Participant annual income	
Basic demographics	*< \$21,000*	11 (52.4)
	≥ \$21,000	10 (47.6)
	Preferred language	
	Spanish	20 (95.2)
	English	1 (4.8)
	People living in home	
	1-2	4 (19.0)
	3-4	9 (42.9)
	>4	8 (38.1)
	Farmworkers living in home	
Type of household resident	*1*	1 (4.8)
	2	2 (9.5)
	3	3 (14.3)
	Children living in home	
	0	4 (19.1)
	1-2	2 (57.1)
	3-4	5 (23.8)
	Indoor pets	
	0	18 (85.7)
	1	2 (9.5)
	4	1 (4.8)
Household pets	Pets moving in and out	
	0	18 (85.7)
	1	2 (9.5)
	4	1 (4.8)

Table 5-2: Kruskal-Wallis Test Associations Between Categorical Household Member Characteristics and Bifenthrin Concentrations in House Dust

Household Member			**Bifenthrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*P*
Basic demographics	Participant education						
	<12 years	17 (81.0)	ND	33.42	2241.71	0.94	0.33
	≥12 years	4 (19.0)	ND	ND	213.78		
	Participant annual income						
	< $21,000	11 (52.4)	ND	ND	2241.71	0.21	0.65
	≥ $21,000	10 (47.6)	ND	49.51	1001.75		
	Preferred language						
	Spanish	20 (95.2)	ND	23.78	2241.71	0.80	0.37
	English	1 (4.8)	ND	ND	ND		

ND-non-detectable

Table 5-3: Spearman Rank Correlations Between Continuous Household Member Characteristics and Bifenthrin Concentrations in House Dust

Household Member		**Spearman's Rank**	
Category	*Characteristic*	*r*	*p*
Type of household resident	Square footage of home	0.26	0.27
	People living in the home	0.35	0.12
	People per square footage	-0.07	0.77
	Farmworkers living in the home	0.24	0.30
	Farmworkers per square footage	0.03	0.92
	Children living in the home	0.29	0.19
	Children per square footage	0.13	0.57
Household pets	Indoor pets	-0.12	0.59
	Indoor pets per square footage	-0.15	0.54
	Pets moving in and out	0.03	0.88
	Pets moving in and out per square footage	0.02	0.92

Table 5-4: Kruskal-Wallis Test Associations Between Categorical Household Member Characteristics and Permethrin Concentrations in House Dust

Household Member			**Permethrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Basic demographic	Participant education						
	<12 years	17 (81.0)	ND	482.73	5400.14	0.65	0.42
	≥12 years	4 (19.0)	183.45	1503.04	3608.18		
	Participant annual income						
	< $21,000	11 (52.4)	183.45	476.97	5400.14	0.04	0.83
	≥ $21,000	10 (47.6)	ND	539.61	3608.18		
	Preferred language						
	Spanish	20 (95.2)	ND	509.18	5400.14	0.44	0.51
	English	1 (4.8)	450.11	450.11	450.11		

ND-non-detectable

Table 5-5: Spearman's Rank Correlations Between Continuous Household Member Characteristics and Permethrin Concentrations in House Dust

Household Member		**Spearman's Rank**	
Category	*Characteristic*	*r*	*p*
Type of household resident	Square footage of home	-0.31	0.37
	People living in the home	-0.19	0.42
	People per square footage	0.004	0.99
	Farmworkers living in the home	-0.14	0.54
	Farmworkers per square footage	0.06	0.81
	Children living in the home	-0.35	0.11
	Children per square footage	-0.24	0.31
Household pets	Indoor pets	0.18	0.44
	Indoor pets per square footage	0.19	0.43
	Pets moving in and out	0.02	0.94
	Pets moving in and out per square footage	0.04	0.86

5.3.2 Household Behaviors and Pesticide Concentrations

5.3.2.1 Summary of Household Behaviors

For farmworker hygiene/ take-home behaviors, it was observed that most of the farmworkers removed their shoes and changed their clothes right away upon arriving home, while the time until showering varied. The level of cleaning and maintenance of the home was generally quite high. Most of the homes were not visibly dusty and had been cleaned either that day or within the last week. About half of the homes reported cleaning their floors everyday using dry methods. For characteristics related to temperature control and ventilation, it was found that most homes opened doors and windows on a daily basis and over half of the homes changed their air filters at least once or twice a month. No heating was utilized in almost half of the homes, but in most homes, cooling was utilized at least part of the year. The summary of household behaviors can be viewed in Tables 5-6 and Table 5-7.

5.3.2.2 Household Behaviors and Bifenthrin in House Dust

For farmworker hygiene/ take-home behaviors, some interesting trends were observed. First, households in which the farmworker reported removing his or her shoes right away upon arriving home had statistically significant higher levels of bifenthrin in the house dust compared to homes in which the farmworker reported removing shoes before arriving home or several hours after arriving home (p=0.04) (Table 5-6), which was confirmed with pair-wise comparisons (Table 5-10). Associations between all other household behaviors and concentrations of in bifenthrin house dust were not statistically significant. Expectedly, households in which the farmworker reported changing clothes just before bed had higher levels of bifenthrin in house dust (p=0.28). In addition, when farmworkers showered either several house after arriving home or just before bed, bifenthrin was higher in the house dust (p=0.60) (Table 5-6).

For the household behaviors related to cleaning and maintenance of the home, it was found that the few households that were visibly dusty had higher levels of bifenthrin in the house dust, although the home with the highest level was not visibly dusty (p=0.33). Houses that had been cleaned within the past week had overall higher levels of bifenthrin in the house dust compared to houses cleaned over one week ago and houses cleaned that day, although the maximum bifenthrin level was found in a home that was cleaned that day (p=0.22). Less compelling findings included overall higher levels of bifenthrin in house dust in homes where the family cleaned the floor less frequently (p=0.56) and using dry methods to clean the floors (p=0.74) (Table 5-6). For behaviors related to temperature control and ventilation, the most interesting finding was that homes that either never opened their windows and doors, or did so on a daily basis, had higher levels of bifenthrin in house dust compared to those that opened their windows so once week or week or once a month (p=0.29). Less prominent findings included that of increased bifenthrin in the house dust for homes that changed their air filters more frequently (p=0.99), never used heating (p=0.32), and used cooling more frequently (p=0.48) (Table 5-6).

5.3.2.3 Household Behaviors and Permethrin in House Dust

Farmworker hygiene/take-home behaviors revealed the significant finding that the time since the most recent house cleaning was associated with permethrin levels in house dust (p=0.02) (Table 5-7). Pairwise comparisons revealed that having cleaned the house more than a week prior was associated with significantly higher levels of permethrin in the house dust compared to those that had cleaned the house within the past week (Table 5-10). All other findings were not statistically significant. Homes in which the farmworker removed his or her shoes before arriving home or right away upon arriving home had higher levels of permethrin in the house dust compared to those that removed shoes several house later (p=0.20). No differences were seen based on time until farmworker changed his or her clothes (p=0.50), or showered (p=0.61). Other cleaning and maintenance behaviors were not well associated with permethrin in house dust, including whether or not the house was visibly dusty (p=0.57), frequency of cleaning floors (p=0.97), and whether or not dry methods were used to clean the floors (p=0.82). For behaviors related to temperature control and ventilation, it was unexpectedly found that changing air filters more frequently was associated with higher levels of permethrin in house dust (p=0.12). Less notable was the finding that homes that opened doors and windows once a week had higher permethrin levels compared to those that did so either less or more frequently (p=0.44). Finally, no differences were observed based on the number of months of heating (p=0.97) or cooling (p=0.74) (Table 5-7).

Table 5-6: Kruskal-Wallis Test Associations Between Household Behaviors and Bifenthrin Concentrations in House Dust

Household Behavior			**Bifenthrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Farmworker hygiene/take-home behaviors	Time until farmworker removes shoes					6.36	**0.04**
	Before arriving home	1 (4.8)	ND	ND	ND		
	Right upon arriving home	15 (71.4)	ND	155.14	2241.71		
	Several hours after home	5 (23.8)	ND	ND	ND		
	Time until farmworker changes clothes					3.87	0.28
	Before arriving home	2 (9.5)	ND	ND	ND		
	Right upon arriving home	12 (57.1)	ND	ND	1015.89		
	Several hours after home	5 (23.9)	ND	ND	368.50		
	Just before bed	2 (9.5)	186.80	1214.25	2241.71		
	Time until farmworker showers					1.02	0.60
	Right upon arriving home	9 (42.8)	ND	ND	397.98		
	Several hours after home	6 (28.6)	ND	191.32	2227.57		
	Just before bed	6 (28.6)	ND	100.47	293.53		
Cleaning and maintenance of home	House visibly dusty					2.24	0.33
	No	16 (76.2)	ND	ND	2241.71		
	Somewhat	2 (9.5)	ND	84.64	186.80		
	Yes	3 (14.3)	65.60	540.75	1015.89		
	Most recent house cleaning					3.06	0.22
	That day	8(38.1)	ND	ND	2241.71		
	Within 1 week	10(47.6)	ND	139.69	1015.89		
	Over 1 week ago	3 (14.3)	ND	ND	186.8		
	Yes	14 (66.7)	ND	39.87	1015.89		

Bold signifies p<0.05; ND- non-detectable

Table 5-6: Kruskal Wallis Test Associations between Household Behaviors and Bifenthrin Concentrations in House Dust (continued)

Household Behavior			**Bifenthrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Cleaning and maintenance of home	Frequency of floor cleaning						
	Everyday	12(47.1)	ND	ND	224.71	1.14	0.56
	Several times a week	6 (28.6)	ND	84.64	397.98		
	Once a week	3 (14.3)	ND	213.78	1015.89		
	Using dry methods to clean floor						
	No	7 (33.3)	ND	ND	2241.71	0.10	0.74
	Yes	14 (66.7)	ND	39.87	1015.89		
Temperature control and ventilation	Frequency of opening doors and windows						
	Never	2 (9.5)	ND	206.06	397.98	3.75	0.29
	About once a month	2 (9.5)	ND	ND	ND		
	About once a week	2 (9.5)	ND	ND	ND		
	Everyday	15 (71.5)	ND	65.60	2241.71		
	Frequency of changing air filters						
	A few times per year	5 (23.8)	ND	ND	383.98	0.02	0.99
	About once or twice a month	14 (66.7)	ND	23.78	2241.71		
	About once or twice a week	2 (9.5)	ND	100.47	186.80		
	Months of heating						
	0	9 (42.9)	ND	155.14	2241.71	2.29	0.32
	1-6	7 (33.3)	ND	ND	213.78		
	7-12	5 (23.8)	ND	ND	1015.89		
	Months of cooling						
	1-6	14 (66.7)	ND	ND	2241.71	0.50	0.48
	7-12	6 (28.6)	ND	110.37	1015.89		
	Decline to answer	1 (4.8)	NA	NA	NA		

NA- not applicable; ND- non-detectable

Table 5-7: Kruskal-Wallis Test Associations between Household Behaviors and Permethrin Concentrations in House Dust

Household Behavior			**Permethrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Farmworker hygiene/take-home behaviors	Time until farmworker removes shoes					3.23	0.20
	Before arriving home	1 (4.8)	1497.03	1497.03	1497.03		
	Right upon arriving home	15 (71.4)	ND	528.02	3631.29		
	Several hours after home	5 (23.8)	ND	191.3	5400.14		
	Time until farmworker changes clothes					2.34	0.50
	Before arriving home	2 (9.5)	1497.03	1497.03	1497.03		
	Right upon arriving home	12 (57.1)	ND	476.97	3608.18		
	Several hours after home	5 (23.9)	ND	619.63	5400.14		
	Just before bed	2 (9.5)	482.73	2057.01	3631.29		
	Time until farmworker showers					0.99	0.61
	Right upon arriving home	9 (42.8)	428.43	528.02	3608.18		
	Several hours after home	6 (28.6)	ND	479.85	5400.14		
	Just before bed	6 (28.6)	ND	490.05	3631.29		
Cleaning and maintenance of home	House visibly dusty					1.14	0.57
	No	16 (76.2)	183.45	486.54	5400.14		
	Somewhat	2 (9.5)	ND	941.73	3631.29		
	Yes	3 (14.3)	ND	266.84	528.02		
	Most recent house cleaning					8.28	**0.02**
	That day	8 38.1)	ND	463.54	2455.86		
	Within 1 week	10(47.6)	ND	539.61	1497.03		
	Over 1 week ago	3 (14.3)	3608.18	3631.29	5400.14		

Bold signifies p<0.05; ND- non-detectable

Table 5-7: Kruskal-Wallis Test Associations between Household Behaviors and Permethrin Concentrations in House Dust (continued)

Household Behavior			**Permethrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Cleaning and maintenance of home	Frequency of floor cleaning						
	Everyday	12 (47.1)	ND	505.37	3631.29	0.06	0.97
	Several times a week	6 (28.6)	183.45	476.57	5400.14		
	Once a week	3 (14.3)	ND	551.21	1497.03		
	Using dry methods to clean floor						
	No	7 (33.3)	ND	ND	7 (33.3)	0.05	0.82
	Yes	14 (66.7)	ND	39.87	14 (66.7)		
Temperature control and ventilation	Frequency of opening doors and windows						
	Never	2 (9.5)	428.88	445.84	462.79	2.68	0.44
	About once a month	2 (9.5)	450.11	2029.15	3608.18		
	About once a week	2 (9.5)	183.45	330.21	476.97		
	Everyday	15 (71.5)	ND	551.21	5400.14		
	Frequency of changing air filters						
	A few times per year	5 (23.8)	ND	462.79	2454.86	4.22	0.12
	About once or twice a month	14 (66.7)	ND	486.54	5400.14		
	About once or twice a week	2 (9.5)	3608.18	3619.74	3631.29		
	Months of heating						
	0	9 (42.9)	183.45	490.34	3631.29	0.06	0.97
	1-6	7 (33.3)	ND	528.02	3608.18		
	7-12	5 (23.8)	ND	462.79	5400.14		
	Months of cooling						
	1-6	14 (66.7)	183.45	479.85	5400.14	0.11	0.74
	7-12	6 (28.6)	ND	509.18	2454.86		

ND-non-detectable

5.3.3 Housing Structure Characteristics and Pesticide Concentrations

5.3.3.1 Summary of Housing Structure Characteristics

Almost half of the homes were less than 1,000 ft^2, and about two-thirds of the homes were at least 10 years old. About 80% of the homes had at least partial ground coverage in the yard and about 62% had at least some carpet in their house, not including doormats. While over half of the homes had outdoor mats in front of at least some of the doors of the house, the majority of the homes did not have indoor mats. Even though most of the homes did not have heating, almost all used central air conditioning. Two-thirds of the homes had double-paned windows. The summary of housing structural characteristics can be seen in Table 5-8 and Table 5-9.

5.3.3.2 Housing Structure Characteristics and Bifenthrin in House Dust

Associations for bifenthrin levels with bigger homes (p=0.72) and homes older than 10 years (p=0.38) were not notable (Table 5-8). Of those characteristics related to ground and floor coverings, having carpet in the house was associated with higher levels of bifenthrin the house dust (p=0.09). Bifenthrin associations with ground coverage in the yard (p=0.38), mats outside the doors (p=0.48), and mats inside the doors (p=0.63) were all weaker findings (Table 5-8). Of the characteristics related to temperature control and ventilation, having double window panes was associated with higher levels of bifenthrin (p=0.20), while less compelling findings included higher bifenthrin in homes with at least partial window air conditioning compared to central air conditioning (p=0.55) and using central heat (p=0.63) (Table 5-8).

5.3.3.3 Housing Structure Characteristics and Permethrin in House Dust

Permethrin levels were not well associated with house size (p=0.47) and age (p=0.79) (Table 5-9). Of those characteristics related to ground and floor coverings, doors with outdoor mats showed a significant association with house dust concentrations (p=0.02) (Table 5-9). Pair-wise comparisons revealed that having no mats outside of any of the doors was associated with higher permethrin in house dust, compared to having mats outside of some or all doors (Table 5-10). A similar association between doors with indoor mats and permethrin in house dust was also seen, and this association was nearly significant (p=0.07). Less prominent findings included associations between permethrin in house dust and no yard coverage (p=0.94) and having carpet (p=0.97) (Table 5-9). Of the characteristics related to temperature control and ventilation, higher levels of permethrin were found in homes with double window panes (p=0.39), window air conditioning compared to central air conditioning either solely or partially (p=0.44), and in homes with central heat versus using a space heater or not having heat at all (p=0.65) and (Table 5-9).

Table 5-8: Kruskal-Wallis Test Associations Between Housing Structure Characteristics and Bifenthrin Concentrations in House Dust

Housing Structure			**Bifenthrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	***Characteristic***	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
House size and age	House Square Footage						
	<1,000 square feet	9 (42.9)	ND	ND	293.53	0.66	0.72
	1,000-2,000 square feet	6 (28.6)	ND	84.64	2241.71		
	>2,000 square feet	5 (23.8)	ND	65.60	397.98		
	House ≥10 years old						
	No	6 (28.6)	ND	ND	397.98	1.92	0.38
	Yes	14 (66.7)	ND	110.37	2241.71		
Ground and floor coverings	Yard Coverage						
	None	4 (19.1)	ND	49.51	186.80	3.11	0.38
	≤ Half	12 (57.1)	ND	13.96	2241.71		
	>Half	5 (23.8)	ND	ND	155.14		
	Carpet in House						
	No	8 (38.1)	ND	ND	368.50	2.96	0.09
	Yes	13 (61.9)	ND	155.14	2241.71		
	Doors with outdoor mats						
	None	7 (33.3)	ND	ND	368.50	1.47	0.48
	Some	5 (23.8)	ND	186.80	2241.71		
	All	8 (38.1)	ND	ND	1015.89		
	Doors with indoor mats						
	None	17 (81.0)	ND	33.42	2241.71	0.93	0.63
	Some	2 (9.5)	ND	100.47	186.80		
	All	1 (4.8)	ND	ND	ND		

ND- non-detectable

Table 5-8: Kruskal-Wallis Test Associations Between Housing Structure Characteristics and Bifenthrin Concentrations in House Dust (continued)

Category	***Housing Structure*** *Characteristic*	*n (%)*	**Bifenthrin Concentration (ng/g)** *Min*	*Median*	*Max*	**Kruskal-Wallis Test** χ^2	*p*
Temperature control/ ventilation	Type of cooling						
	Central air conditioning	17 (81.0)	ND	ND	2241.71		
	Window air conditioning	2 (9.5)	65.60	126.20	186.80	2.12	0.55
	Both central and window	1 (4.8)	213.78	213.78	213.78		
	Type of heating						
	Central heat	2 (9.5)	ND	206.06	397.98		
	Space heater or other	5 (23.8)	ND	ND	213.78	2.29	0.32
	No heating	14 (66.7)	ND	94.28	2241.71		
	Window panes						
	Single	7 (14)	ND	ND	213.78	1.66	0.20
	Double	14 (66.7)	ND	49.51	2241.71		

ND- non-detectable

Table 5-9: Kruskal-Wallis Test Associations Between Housing Structure Characteristics and Permethrin Concentrations in House Dust

Category	***Housing Structure*** *Characteristic*	*n (%)*	Permethrin Concentration (ng/g) *Min*	*Median*	*Max*	Kruskal-Wallis Test χ^2	*p*
House size and age	House square footage						
	<1,000 square feet	9 (42.9)	191.30	551.21	5400.14	1.53	0.47
	1,000-2,000 square feet	6 (28.6)	ND	486.54	1497.03		
	>2,000 square feet	5 (23.8)	183.45	462.79	619.63		
	House ≥10 years old						
	No	6 (28.6)	183.45	445.61	5400.14	0.47	0.79
	Yes	14 (66.7)	ND	539.61	3631.29		
Ground and floor coverings	Yard coverage						
	None	4 (19.1)	191.3	528.02	3631.29	0.11	0.94
	≤ Half	12 (57.1)	ND	482.73	3608.18		
	>Half	5 (23.8)	ND	490.34	5400.14		
	Carpet in house						
	No	8 (38.1)	ND	534.87	5400.14	0.001	0.97
	Yes	13 (61.9)	ND	490.34	3625.29		
	Doors with outdoor mats						
	None	7 (33.3)	490.34	941.73	5400.14	9.89	**0.02**
	Some	5 (23.8)	428.43	482.73	3631.29		
	All	8 (38.1)	ND	445.84	1497.03		
	Doors with indoor mats						
	None	17 (81.0)	ND	490.34	5400.14	6.94	0.07
	Some	2 (9.5)	1497.03	2564.16	3631.29		
	All	1 (4.8)	183.45	183.45	183.45		

Bold signifies p<0.05; ND- non-detectable

Table 5-9: Kruskal-Wallis Test Associations Between Housing Structure Characteristics and Permethrin Concentrations in House Dust (continued)

Housing Structure			**Permethrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*Characteristic*	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*
Temperature control/ ventilation	Type of cooling						
	Central air conditioning	17 (81.0)	ND	482.73	5400.14	2.72	0.44
	Window air conditioning	2 (9.5)	528.02	2079.65	3631.29		
	Both central and window	1 (4.8)	551.21	551.21	551.21		
	Type of heating						
	Central heat	2 (9.5)	462.79	702.26	941.73	1.65	0.65
	Space heater or other	5 (23.8)	191.3	528.02	2454.86		
	No heating	14 (66.7)	183.45	554.99	3631.29		
	Window panes						
	Single	7 (14)	ND	428.88	3631.29	0.74	0.39
	Double	14 (66.7)	ND	509.18	5400.14		

ND- non-detectable

Table 5-10: Pairwise Comparisons* of Household Behaviors or Housing Structure Characteristics and Pesticide Concentrations in House Dust with and Without Bonferroni Corrections

Variable	Outcome	Comparison	p-value *Bonferroni Correction*	p-value *No Correction*	Pairwise Comparison Conclusion
Time until farmworker removes shoes	Bifenthrin in house dust	Before arriving home vs. right upon arriving home	0.63	0.31	Higher when farmworker removes shoes right away upon arriving home
		Before arriving home vs. several hours later	-		
		Right upon arriving home vs. several hours later	0.05	**0.02**	
Most recent house cleaning	Permethrin in house dust	Over 1 week ago vs. that day	**0.04**	**0.01**	Higher when most recent cleaning > 2 weeks ago
		Over 1 week ago vs. within 1 week	**0.02**	**0.007**	
		Within 1 week vs. that day	0.86	0.29	
Mats outside doors	Permethrin in house dust	All doors vs. some doors	0.85	0.28	Higher when no mats outside of any doors
		All doors vs. no doors	**0.02**	**0.006**	
		Some doors vs. no doors	0.11	0.32	

*Based on significant associations from Table 5-4 – Table 5-9
Bold signifies p<0.05

5.3.4 Distance from Home to Agricultural Field and Pesticide Concentrations

5.3.4.1 Reported and Measured Distances from Home to Agricultural Field

When participants were asked to report the distance from their home to the nearest agricultural field, 11 (55%) reported they were <0.5 mile from a field, four (20%) reported they were 0.5-1 mile from a field, and 5 (25%) reported they were >1 mile from a field (Table 5-11). Yet, when measured using GoogleEarth® (Google Inc., 2015), 100% of the homes were <1 mile from a field. Specifically, 17 (85%) were <0.5 mile from a field and 3 (15%) were 0.5-1 mile from a field (Table 5-11). For the measured distances, the range was 0.01-0.84 mile and the median distance was 0.16 mile (Table 5-11). When the measured distances were placed into categories of 200 feet, 400 feet, and 800 feet, four homes (20%) were <200 feet from a field, one home (5%) was 200-400 feet, five homes (25%) were >400-800 feet, and 10 homes (50%) were >800 feet (Table 5-12).

5.3.4.2 Associations Between Distance from Home to Field and Bifenthrin Concentrations

Results from the Kruskal-Wallis test revealed a significant association between the participant-reported distance to the closest field with bifenthrin concentrations in house dust (p=0.04) (Table 5-12) and the pair-wise comparison elucidated that bifenthrin concentrations were significantly higher in homes reported to be <1 mile from an agricultural field (Table 5-13). For the measured distance to the closest field, bifenthrin concentrations in the house dust was not significant (p=0.09); since only 2 categories were applicable, the difference was inevitably between homes <0.5 miles and ≥0.5 miles away from a field (Table 5-12). Very weak associations were seen for bifenthrin in house dust by measured distances in categories of 200 feet, 400 feet and 800 feet (p=0.82) or <200 feet and ≥200feet (p=0.76) (Table 5-12). Kruskal-Wallis tests did not reveal notable associations between permethrin concentrations in house dust and the distance from home to nearest field when either reported by participant or measured by GoogleEarth® (Google Inc., 2015) (Table 5-12). Additionally, bifenthrin in house dust was not well correlated with the measured distance from home to field (r=-0.17) (Table 5-11).

5.4.3.3 Associations Between Distance from Home to Field and Permethrin Concentrations

Kruskal-Wallis tests did not reveal notable associations between permethrin concentrations in the house dust and the distance from home to field when either reported by participant (p=0.68) or measured by GoogleEarth® (Google Inc., 2015) (p=0.64) (Table 5-11). Weak associations were seen for permethrin in house dust by measured distances in categories of 200 feet, 400 feet and 800 feet (p=0.43) or <200 feet and ≥200feet (p=0.92) (Table 5-11). Additionally, permethrin in house dust was not notably correlated with the distance from home to field (r=0.09) (Table 5-12).

Table 5-11: Description of Measured Distances from Homes to Nearest Field and Spearman's Correlations with Concentrations of Bifenthrin and Permethrin in House Dust

Reported Distances		**Measured** Distances		Percentile Distribution of **Measured** Distances (mi)					Spearman's Correlation (r) between House Dust Levels and **Measured** Distances	
Category (mi)	n (%)	Category (mi)	n (%)	Min	*25th %*	*50th %*	*75th %*	*Max*	*Bifenthrin*	*Permethrin*
<0.5	11 (55)	<0.5	17 (85%)	0.01	0.08	0.13	0.22	0.43	-0.17	0.09
0.5-1	4 (20)	0.5-1	3(15%)	0.50	0.60	0.69	0.77	0.84		
>1-3	5 (25)	>1-3	0(0%)	-	-	-	-	-		
Overall	20 (100%)	Overall	20 (100%)	0.01	0.08	0.16	0.34	0.84		

Table 5-12: Pairwise Comparison of Reported Distance to Nearest Field for Bifenthrin Concentration in House Dust

Distance from field to home (mile)		**Bifenthrin Concentration (ng/g)**			**Kruskal-Wallis Test**		**Permethrin Concentration (ng/g)**			**Kruskal-Wallis Test**	
Category	*n (%)*	*Min*	*Median*	*Max*	χ^2	*p*	*Min*	*Median*	*Max*	χ^2	*p*
Reported											
<0.5 mi	11 (55.0)	ND	ND	1015.89			ND	462.79	3608.18		
0.5- 1 mi	4 (20.0)	ND	39.87	368.50	6.51	**0.04**	528.02	1058.33	5400.14	0.77	0.68
>1 mi	5 (25.0)	ND	186.8	2241.71			428.43	482.73	3631.29		
Measured (version 1)											
<0.5 mi	17 (85.0)	ND	ND	1015.89			ND	490.34	5400.14		
0.5- 1 mi	3 (15.0)	ND	213.78	2241.71	2.88	0.09	428.88	482.73	551.21	0.23	0.64
>1 mi	*0 (0.0)*	NA	NA	NA			NA	NA	NA		
Measured (version 2)											
< 200 feet	*4 (20.0)*	ND	100.47	2241.71			183.45	479.85	3631.29		
200 - 400 feet	*1 (5.0)*	ND	ND	ND	0.91	0.82	ND	ND	ND		
>400 -800 feet	5 (25)	ND	33.42	397.98			428.43	528.02	5400.14	2.74	0.43
>800 feet	10 (50)	ND	84.64	1015.89			ND	520.78	2454.86		
Measured (version 3)											
<200 feet	4 (20.0)	ND	100.47	2241.71	0.09	0.76	183.45	479.85	3631.29	0.009	0.92
≥200feet	16 (80.0)	ND	23.78	1015.89			ND	509.18	5400.14		

Bold signifies p<0.05

NA- not applicable; ND- non-detectable

Table 5-13: Kruskal-Wallis Test Associations Between Distances from Homes to Nearest Field and Concentrations of Bifenthrin and Permethrin in House Dust With and Without Bonferroni Correction*

Variable	Outcome	Comparison	p-value Bonferroni correction	p-value No correction	Pairwise Comparison Conclusion
Reported distance to closest field	Bifenthrin in house dust	<0.5 mile vs. 0.5-1mile	0.64	0.21	Significantly higher when closet field < 1 mile from home
		<0.5 mile vs. >1mile	0.13	**0.05**	
		0.5-1mile vs. >1mile	0.12	**0.05**	

*Based on significant associations from Table 5-11– Table 5-12
Bold signifies p<0.05

5.3.5 Residential Pesticide Use and Pesticide Concentrations

5.3.5.1 Summary of Residential Pesticide Use

Residential pesticide use was reported in 16 of the 21 homes. 13 of these homes reported using an insecticide to control for cockroaches, flies, or other insects, two of these homes reported using an herbicide to control weeds (in which one of these homes also reported using an insecticide), and two homes reported that they had professional application in their yard and were unable to identify for what purpose. Of the five homes in which residential pesticide use was not reported, four did not use any pesticides, and one declined to answer this particular question. The active ingredients could be identified in 10 of the 16 homes that used pesticides; of the remaining six homes, two had professional applications and did not know the ingredients used and four could not remember the product they used. A full description of the active ingredients of the residential pesticides used in each home can be seen in Table 5-14.

5.3.5.2 Associations between Residential Pesticide Use and Bifenthrin Concentrations

None of the homes reported using any products with bifenthrin as an active ingredient (Table 5-14). Nonetheless, since six homes that did use residential pesticides did not know the active ingredients of the products used (either by the family or professionally applied), the “don’t know” responses were handled in the four ways described previously. After the “don’t know” responses were assumed to be “yes” responses, the median levels of bifenthrin in house dust were higher compared to homes that definitely did not use the pesticide, but this finding was not significant (p=0.22). After the “don’t know” responses were made into its own unique category, the overall bifenthrin levels for the “don’t know” homes were higher compared to “yes” or “no” homes, but this finding was not significant (p=0.22). Excluding the “don’t know” responses all together, along with assuming the “don’t know responses” were “no” responses, did not allow for observation of trends or for testing of differences because since none of the homes reported using bifenthrin in the home, only responses in the “no” category remained. (Table 5-15).

5.3.5.3 Associations between Residential Pesticide Use and Permethrin Concentrations

Permethrin was definitively used in four homes (Table 5-14). For the six homes that could not identify the active ingredients of the pesticides used residentially, the “don’t know” responses were handled in the four ways described previously. All four methods of handling “don’t know” responses yielded similar concentrations in the house dust for all categories, and any differences were not statistically significant (Table 5-16).

Table 5-14: Description of Active Ingredients in Residential Pesticides Used (N=21)

Ingredient(s)	**n**	**Pesticides used?**	**Insecticides used?**	**Permethrin used?**	**Bifenthrin used?**
Aliphatic hydrocarbon, d-trans allethrin, permethrin, hydrocarbon propellant	1	Yes	Yes	Yes	No
Boric Acid	1	Yes	Yes	No	No
Deltamethrin, quartz	1	Yes	Yes	No	No
Hydromethylnon	1	Yes	Yes	No	No
Isobutane, propane, synthetic iso-paraffinic hydrocarbons, d-phenothrin, tetramethrin	1	Yes	No	No	No
Permethrin, pyrethrum extram, technical piperonyl butoxide	3	Yes	Yes	Yes	No
Potassium hydroxide, isopropylamine salt of glyphosate	1	Yes	No	No	No
Water, butane, propane, distillates, isobutane, allethrin, d-phenothrin	1	Yes	Yes	No	No
Don’t know – family applied	4	Yes	Yes	Don’t know	Don’t know
Don’t know –professionally applied	2	Yes	Don’t know	Don’t know	Don’t know
No pesticide used	4	No	No	No	No
Declined to answer	1	Don’t know	Don’t know	Don’t know	Don’t know

Table 5-15: Kruskal-Wallis Test Associations between Residential Pesticide Use and Bifenthrin in House Dust According to Handling of "Don't know" Responses

Assumption About "Don't know" Responses	**Bifenthrin Concentration (ng/g)** *Min*	*Median*	*Max*	**p-value**
"Don't know" responses assumed to be "yes" (n=21)				
No (n=14)	ND	ND	1015.89	0.22
Yes (n=7)	ND	155.14	2241.71	
"Don't know" responses excluded (n=14)				
No (n=14)	ND	ND	1015.89	-
Yes (n=0)	NA	NA	NA	
"Don't know" responses made its own category (n=21)				
No (n=14)	ND	ND	1015.89	0.22
Yes (n=0)	NA	NA	NA	
Don't know (n=1)	ND	155.14	2241.71	
"Don't know" responses assumed to be "no" (n=21)				
No (n=21)	ND	ND	2241.71	-
Yes (n=0)	NA	NA	NA	

- could not K-W test "don't know" excluded or when "don't know" was assumed to be "no" because only one category remained (i.e., "yes" answer never given)

. no responses in the category

NA- not applicable; ND- non-detectable

Table 5-16: Kruskal-Wallis Test Associations[#] between Residential Pesticide Use and Permethrin in House Dust According to Handling of "Don't know" Responses

Assumption About "Don't know" Responses	**Permethrin Concentration (ng/g)** *Min*	*Median*	*Max*	**p-value**
"Don't know" responses assumed to be "yes" (n=21)				
No (n=10)	ND	502.50	5400.14	0.86
Yes (n=11)	ND	490.34	2454.86	
"Don't know" responses excluded (n=14)				
No (n=10)	ND	502.5	5400.14	0.94
Yes (n=4)	428.88	541.21	2454.86	
"Don't know" responses made its own category (n=21)				
No (n=10)	ND	502.50	5400.14	
Yes (n=4)	428.88	541.21	2454.86	0.94
Don't know (n=7)	ND	490.34	1497.03	
"Don't know" responses assumed to be "no"				
No (n=17)	ND	490.34	5400.14	0.86
Yes (n=4)	428.88	541.21	2454.86	

ND- non-detectable

5.4 Discussion

5.4.1 Influence of Farmworker Behaviors on Agricultural Pesticide Levels in House Dust

Overall in the current study, factors related to the farmworkers themselves, and their behaviors, were not among the strongest household-level risk factors for increased levels of either bifenthrin or permethrin in the farmworkers' house dust. First, the basic demographics of the farmworkers, including education level, household annual income, and preferred language were all not well associated with levels of bifenthrin or permethrin in house dust. Secondly, the classic farmworker hygiene/ take-home behaviors of removing shoes, changing clothes, and showering promptly upon arriving home, were not associated with reduced agricultural pesticide levels in house dust levels. For bifenthrin, the only significant finding among such behaviors was that farmworkers removing shoes right away upon arriving home actually resulted in higher levels of bifenthrin in house dust when compared to the removing of shoes before arriving home or several hours after being home (p=0.02 for pairwise comparison, p=0.05 after bonferroni correction). Similarly for permethrin, removing shoes earlier was also associated with higher levels in the house dust, although this finding was not significant (p=0.20).

Overall, higher bifenthrin in house dust was found when farmworkers changed clothes later (p=0.28) and showered later (p=0.60), although the maximum concentrations were found for participants who changed clothes and showered earlier upon arriving home. Given the combination of the inconsistency of the trend and the statistical insignificance of the association, caution should be taken in suggesting that a relationship exists between these behaviors and bifenthrin house dust level. For permethrin, levels in the farmworkers' house dust were not at all associated with the time before farmworkers changed clothes (p=0.50) or showered (p=0.61). These findings suggest that the act of farmworkers removing shoes, changing clothes, and showering may not effectively reduce agricultural pesticide levels in the home.

The suggestion of removing shoes before or right away upon arriving home to reduce track-in of contaminants is common in the peer-reviewed literature (Simcox et al., 1995; McCauley et al., 2001; Franzblau et al., 2009; Salvatore et al., 2009). Among studies that quantitatively evaluated the effect of this behavior on contaminant levels in the house dust, some reported that removing shoes was positively associated with lower levels of contaminants in the house dust (Nishioka et al. 1999b; Lozier et al., 2012; Whitehead et al., 2013). However, others reported that the effect of shoe removal was either not well associated, or that it varied (McCauley et al. 2003; Hunt et al., 2006; Thompson et al., 2008; Coronado et al., 2012; Sbihi et al., 2013).

In Hunt et al. (2006), which tested the mass of soil track-in using different types of footwear, it was reported that picking up soil post-deposition can be more pronounced than the initial transfer of dry soil into the home on shoes. The potential to pick up previously deposited soil or dust in the home could be important to the current study because participants in one home reported that farmworkers removed shoes upon arriving home from work as recommended, yet they also put their shoes back on while inside the house and subsequently walked around within the home. Therefore, it is possible that putting shoes back on while still in the home could be a more detrimental behavior, as this could track the contaminant around the house. Although farmworkers may be instructed about behaviors believed to prevent soil track-in, there may still be gaps in their education. It is unclear if this anecdotal evidence represents a widespread education gap. These particular questions could be further assessed in future studies and could provide significant insight on how to improve farmworker education.

Notably, in Sbihi et al. (2013), factors that contributed to the house dust detection of hopanes, a stable and non-volatile tracer of primary vehicular exhaust aerosols in ambient air, reported that the effect of shoe removal varied by city, with correlations in multiple cities matching the direction of the current study. This lends credence to the validity of the finding in the current study, in which house dust levels of bifenthrin, which is also relatively stable and non-volatile, was negatively associated with the timing of the shoe removal.

The importance of changing clothes and showering has similarly been widely emphasized in the peer-reviewed literature (Simcox et al., 1995; Alvanja et al., 1999; Curwin et al., 2002, Thompson et al., 2003; Goldman et al., 2004; Rao et al., 2006; Quandt et al., 2006; Salvatore et al., 2009; Fenske et al., 2013; Quandt et al., 2013). This emphasis may be in response to the USEPA's Worker Protection Standard, which requires that employers of agricultural establishments provide workers with access to water for showering and a clean change of clothes to put on if the worker's garments become contaminated and need to be removed (USEPA, 2016a). Regardless, only a few studies have actually explored whether a relationship exists between these behaviors and agricultural pesticide levels, in the household, and results of these studies have been mixed, rendering the effect of these behaviors unconvincing. Lu et al. (2000) did observe lower agricultural pesticide metabolites in the urine of farmworker's children in homes where the farmworker changed clothes prior to entering the home, although this relationship was not statistically significant. McCauley et al. (2003) found that changing clothes later was associated with higher levels of agricultural pesticides in the house dust, yet no association was observed based on showering later. In a community-wide intervention by Thompson et al. (2008) which largely focused on educating farmworkers about these behaviors, no reduction of agricultural pesticide levels in the house dust or in the urine of household members was observed. Fenske et al. (2002), Arcury et al. (2006), Coronado et al. (2012), and Golla et al. (2012) all found no association between house dust levels of agricultural pesticides and the time when the farmworker changed out of work clothes or showered, in addition, Bradman et al. (2007) found no association between these behaviors and agricultural pesticide levels in the urine of farmworkers' children. A combination of these findings for both bifenthrin and permethrin existed in the current study. This in combination with the mixed results of prior studies suggest that these highly encouraged farmworker behaviors may not play the most influential role in reducing agricultural pesticide levels in the home.

It is notable that the current study had a small sample size, making it difficult to assert whether these findings would be the same with a larger sample size. In addition, the current study relied on self-reported data, making it impossible to confirm that the actual behaviors match the participants' answers. It is worth noting that in a previous study, farmworkers expressed reluctance to shower immediately after work because of folk beliefs that such behavior could lead to adverse health effects such as rheumatism (Arcury et al., 2001). It is possible that the farmworkers may keep these types of beliefs to themselves, or they may answer questions according to their perception of what the interviewer wanted to hear. Nonetheless, the reliance on self-reported data is a limitation that all of the related studies have encountered as well.

5.4.2 Considering Factors Related to the Entire Farmworker Household

Household-level risk factors related to the entire household, such as family-wide behaviors and the physical structure of the house, all contribute to better understanding reasons for the detection of agricultural pesticide levels in the farmworkers' house dust. In the current study, an interesting trend in the house dust was observed for both bifenthrin and permethrin, with respect to the square footage of the home, although the findings were in opposite direction. For bifenthrin, square footage of the home was positively correlated with levels in the house dust (r=0.26, p=0.27). It is possible that the increased level of agricultural pesticides in the house dust occurred because a larger house has a greater area of entry points for which agricultural pesticides can penetrate, although this phenomenon has not been previously explored to the knowledge of the author of this dissertation. On the other hand, for permethrin, a negative correlation was observed between house dust levels and square footage of the home (r=-0.31, p=0.37). Given that Hunt et al. (2006) reported notable potential to pick up previously deposited soil or dust within the home and track it around, families in larger homes could spread pesticides throughout the larger surface area, possibly diluting the concentration of the pesticide in any given sample. The effect of square footage of the home has not been widely explored in the peer-reviewed literature. Previously McCauley et al. (2003) reported a slight correlation between square footage of the home and agricultural pesticide levels in the house dust. In Quandt et al. (2004), although square footage itself was not assessed, pesticide levels in mobile homes versus single family homes were compared, which may be a useful proxy for size since mobile homes almost always have a much smaller square footage than single family homes. In that study, no differences were detected in the house dust levels between the two types of homes. This proxy should be considered with caution because other important differences between mobile homes and single family homes often exist, such as potential holes and cracks in the walls. Given that in the current study, correlations in opposite directions were observed for the two different pesticides studied, it might be useful to further explore the effect of house square footage on the levels of a variety of agricultural pesticides with a wide-range of chemical characteristics.

For bifenthrin in particular, the number of people, farmworkers, and children were all positively correlated with the agricultural pesticide levels in the house dust, but the fact that the number of people in the home was the most compelling ($r=0.35$, $p=0.12$), implies that overall traffic in the house may be most influential. This could suggest that bifenthrin enters the home via take-home/soil track-in, but if this was the case, ground coverings and floor coverings should have decreased track-in. Yet having more ground covered in the yard and having mats inside and outside of the doors were not associated with lower bifenthrin levels in the house dust. Another possibility is that bifenthrin enters the home primarily through air infiltration, and the higher number of people living in the house leads to more traffic in and out of the house causing the doors to open and close more frequently and allowing for soil and dust particles to be resuspended as people around.

In the peer-reviewed literature, two main studies explored the association between number of household residents and agricultural pesticide levels in the house dust (McCauley et al., 2001; Harnly et al., 2009). McCauley et al. (2001) assessed the influence of number of total people and number of farmworkers in the home on agricultural pesticide levels. In that study, it was found that both were positively correlated with concentrations in the house dust, similar to the current study. However, in McCauley et al. (2001), the correlation was stronger for the number of farmworkers in the home compared to number of total people living there, which is opposite of the trend in the current study. It may be notable that the sample size for McCauley et al. (2001) (n=96) is much larger than that of the current study (n=21). It is possible that if the current study had a larger sample size, that the findings would match more closely to those of McCauley et al. (2001). Harnly et al. (2009) also reported a significant relationship between number of farmworkers in the home and levels of agricultural pesticides in the house dust. However, the total numbers of people, including children, were not considered in that study.

In the previous studies by McCauley et al. (2001) and Harnly et al. (2009), the association between the number of farmworkers and agricultural pesticide levels in the house dust were explained to be a function of increased potential of the take-home pathway. Yet, the fact that in the current study, the correlation is stronger for total residents compared to farmworkers could suggest a lesser influence of the take-home pathway of farmworkers from the agricultural fields, and more emphasis on behaviors that include the entire family. It is suggested that, in the future, researchers expand the scope of interventions to reduce agricultural pesticides levels in the home to include factors related to the entire household. Alternatively, researchers may want to explore the possibility of making changes to the house itself, rather than relying on individuals to change their behaviors.

Another interesting finding in the current study was that homes where the residents opened their doors and windows either never or everyday had higher levels of bifenthrin in house dust compared to home where doors and windows were opened about once a week or once a month ($p=0.29$). This provides evidence that air infiltration, and by extension air exfiltration, is an important pathway for bifenthrin transport, and may also insinuate that there is an optimal frequency for opening windows and doors to maximize exfiltration of agricultural pesticides from the home, while also minimizing air infiltration. Another notable finding was that homes with double paned windows had higher bifenthrin levels in house dust ($p=0.20$) which is likely a reflection of the decreased ability for bifenthrin to exfiltrate naturally out of the house, particularly if there is also some contribution of bifenthrin brought into the home from the take-home pathway. In the peer-reviewed literature, the effect of opening doors and windows on the levels of contaminants in the house dust is limited, and the findings have been mixed. Quandt et al. (2004) reported no difference in agricultural pesticide levels in the house dust for homes that always kept their windows closed compared to those that sometimes opened them. Also, in a study by

Nishioka et al. (1999a), which assessed the transport of 2, 4-D from residential lawns into homes, found that spray drift and fine particle intrusion through the opening of doors and windows contributed less to residues on the floor in comparison to track-in behaviors. Another previous study (Egeghy et al., 2005) that focused on lead in house dust reported a positive relationship between opening doors and windows and the concentration of lead in the house dust, concluding that this was indicative of lead being an outdoor contaminant. McCauley et al. (2001) noted the frequency of opening doors and windows as an indicator of ventilation in the home, but did not directly assess the association with agricultural pesticide levels in the house dust. Therefore, it appears that there is high potential for future works to explore the concept of opening doors and windows, and its relationship with pesticide air infiltration in to the home.

For permethrin in the current study, having no outdoor mats ($p=0.02$) or indoor mats ($p=0.07$) were both positively associated with levels in the house dust. This suggests that there is some contribution of the soil track-in pathway into the home for this pesticide. Again, it is important to note that soil track-in is not necessarily limited to farmworkers taking home agricultural pesticides after working in the field. In fact, as discussed earlier, permethrin was not well associated with farmworkers' behaviors related to removing shoes, changing clothes, or showering. Rather, it is possible that permethrin in house dust comes, at least partially, from residential pesticides used outside (e.g., on the lawn, in the backyard) that is subsequently tracked into the house. In this case, for homes where family members spend more time outdoors, there would be in increased track-in of permethrin into the home in the absence of mats outside and inside the doors. In the peer-reviewed literature, the effectiveness of using doormats has been mixed. Nishioka et al., (1996a) found that rubber mats with polypropylene fibers can reduce carpet dust residues up to 33%. Roberts et al. (2007) also suggested the use of commercial-grade mats as an effective way to reduce track-in of contaminants into the home. On the other hand, Ganser (2006) reported that the effectiveness of mats is highly variable and in Simcox et al. (1995), having entry mats was not found to influence pesticides levels in house dust.

Another influential factor regarding permethrin levels was that the sampled homes which changed air filters more frequently were associated with higher levels of permethrin in the house dust ($p=0.12$), possibly supporting the idea that air infiltration contributes to permethrin in the house dust. This is a meaningful finding because families may change their air filters so frequently out of the belief that this is helping to effectively clean their home. Nonetheless, this study suggests that it is more effective to change air filters less frequently. This notion is supported by studies in the peer-reviewed literature that found that less frequent changing of air filters can allow for a “filter cake" effect, which traps particles in the fibers, decreases porosity, and ultimately increases filter efficiency (Miguel et al., 2003; Al-Otoom, 2005).

The fact that sampled families in the current study were motivated to change air filters so frequently also indicates that there is a high level of dustiness in this community, highlighting the relevance of wind-driven particle transport through the air. Future research or intervention studies should further explore the effect of changing air filters, and the optimal frequency of doing so, as this would add value to the understanding of a behavior that could help prevent air infiltration of agricultural pesticides into homes. Based on the findings of the current study, the influence of permethrin in the home may be from a mixture between soil track-in and air infiltration influences.

Due to the fact that permethrin is often an ingredient in formulations of Raid®, a common household pesticide, it is wise to exercise caution about the lack of noted association between reported residential pesticide use and permethrin in the house dust. Lack of associations with reported residential uses could be due to incorrect recollection regarding pesticides used in the home, or it could be an effect of the assumptions made concerning homes where they did not know if bifenthrin or permethrin was applied residentially. Other associations may indirectly suggest a relationship between residential pesticide use and permethrin in the house dust. For example, permethrin levels in house dust were negatively correlated with fewer children in the home ($r= -0.35$, $p=0.12$), while correlations with all other household member groups were weaker and less notable. It is possible that this finding is driven by the fact that families with children may be more wary of using household pesticides, such as Raid®. It is difficult to confirm this theory for the present study, however, because there were only four families without children (19%); one of these families declined to answer whether or not pesticides were used in the home, one family report not using any pesticides, and two families did report using household pesticides. It would have been useful to ask families how frequently they use household pesticides in their home because it is possible that a family with children may be more likely to hesitate to use residential pesticides, yet still do so once in a while. Unfortunately, this could not be captured in the current study.

5.4.3 Effect of Distance from Home to Nearest Agricultural Field

One of the most convincing findings supporting the idea that bifenthrin levels are mostly related to living in an agricultural community, rather than directly from the farmworker status of the family, is the fact that the measured distance from home to the nearest agricultural field was negatively associated with bifenthrin in house dust ($p=0.04$). On the other hand, the distance to the nearest agricultural field was not associated with permethrin levels in house dust which could reflect the influence of residential pesticide applications, or alternatively, could be due to the substantially shorter soil half-life compared to permethrin compared to bifenthrin. The results of these analyses match those in Chapter 4 in which a geographical information systems (GIS) approach was used to assess temporal and spatial associations between agricultural applications and pesticide levels at homes. A moderate association was found between bifenthrin agricultural applications within one-year prior to sampling the farmworkers' homes and bifenthrin levels in the house dust, yet no association between permethrin agricultural applications and permethrin house dust levels was found.

Although a significant association was found between the measured distance to the nearest agricultural field categories (i.e., <0.5 mile, 0.5-1 mile, >1 mile) and bifenthrin levels in the house dust, when the distance was kept as a continuous variable, the Spearman's rank correlation was very weak. Although tests that use a continuous variable generally have higher power, this is only the case when there is a linear relationship between the independent and dependent variables, while categorical tests tend to better capture complex relationships that are not necessarily linear (Pasta, 2009). As such, it was actually more beneficial to categorize the distance variable in this case because it identified <0.5 mile between home and field as an influential cut-off point for levels of bifenthrin in the house dust. Categorical variables can also be more useful from a didactic perspective in which it may be more practical to discuss associations using useful categories (ibid); in the current study, using these particular categorical distances facilitated the comparison between reported distances and measured distances.

Distance between homes and the nearest agricultural field has been widely explored in previous agricultural pesticide studies because it is considered to be an indicator of pesticide drift in either the vapor or particle phase. To the knowledge of the author of this dissertation, 17 previous studies in the peer-reviewed literature assessed the association between the distance from homes to the nearest agricultural field or orchard and pesticide levels in house dust (Table 5-17), and the results of these studies have been quite mixed. Of those 17 studies, nine reported some association between distance and agricultural pesticide levels in the house dust, and those studies concluded that drift from nearby fields is likely factor (Simcox et al., 1995; Loewenherz et al., 1997; McCauley et al., 2001; Quandt et al., 2004; Weppner et al., 2006; Harnly et al., 2009; Coronado et al., 2011; Gunier et al., 2011; Deziel et al., 2013). Five studies did not find any association between distance and agricultural pesticide levels in the house dust (Lu et al., 2000; Fenske et al., 2002; Curwin et al., 2005; Ward et al., 2006; Golla et al., 2012; Lozier et al., 2012). Two studies could not conclude with certainty whether distance was influential due to their study design (Curl et al., 2002; McCauley et al., 2003). One study by Richards et al., (2001) found evidence of drift in outdoor samples, but did not detect an association with pesticide levels inside the home. See Table 5-17 for a full description of 17 previous studies' findings related to distance between the home and nearest agricultural field.

In the previous studies that assessed the relationship between distance and house dust levels of pesticides, diverse conclusions were made regarding the agricultural pesticide transport pathways. Some researchers, such as Richards et al. (2001), Fenske et al. (2002), and Gunier et al. (2011) attributed their findings to pesticide spray drift, while others, such as McCauley et al. (2003), Curwin et al. (2005), and Lozier et al. (2012) concluded that agricultural pesticide levels in the house dust were likely to be due to the take-home pathway. Others believed that both drift through the air and the take-home pathway contributed to the levels of agricultural pesticides in the house dust (Simcox et al., 1995; Ward et al., 2006; Harnly et al., 2009). Finally, others refrained from speculating about the transport pathways at all or about whether proximity to the field was even a primary determinant of agricultural pesticide levels (Loewenherz et al., 1997; Curl et al., 2002; Deziel et al., 2013).

Several of the previous studies that assessed the relationship between home to field distance and agricultural pesticides in house dust used distance categories of 200 feet and 400 feet (for reference: 200 feet= 60.96 meters= 0.038 mile) (Simcox et al., 1995; Loewenherz et al., 1997; Fenske et al., 2002; Weppner et al., 2006). These categories were also considered for the current study; however, no association was observed between house dust levels of either bifenthrin or permethrin and these distance categories. This could be due to the fact that 50% of the homes were >800 feet from a field. In addition, only five homes were within the range of <200 feet or 200-400 feet, making it difficult to compare the findings of this study with previous studies at this level of specificity.

In general, 200 feet is considered the hallmark range for spray drift upon air-blast applications in orchards (Fox et al., 1990), and therefore, air transport beyond this distance is more likely to be due to wind-driven resuspension of contaminated soil particles. For this reason, <200 feet and ≥200 feet and were additionally assessed in this study as cut-off points for differences in household dust levels. No significant difference was observed in the current study for either bifenthrin or permethrin, suggesting that air transport of soil contaminated particles may contribute substantially to agricultural pesticide levels in homes. This notion is supported the modeling results in Chapter 3, which found that a major transport pathway of agricultural pesticides into the house dust of farmworkers' homes was via air infiltration for both pesticides.

The only previous study known to the author that directly postulated that the association between agricultural pesticide levels and the distance to the nearest agricultural field could be a result of wind-driven resuspension of contaminated soil particles was Quant et al. (2004), although in that study only general comparison categories of “adjacent” versus ‘non-adjacent” to field were used. The current study is the first to suggest air transport via soil particles with defined distance categories.

In addition, the fact that bifenthrin is known to strongly adhere to soil particles based on its inherent chemical characteristics provides compelling evidence that the observed association between homes and the nearest agricultural field is rooted in drift of soil particles through the air. Please see Chapter 4 of this dissertation for additional information on the chemical characteristics of bifenthrin.

Additional perspective related to distance from home to field was gained from evaluating the effect of the difference between the participant-reported distances versus the measured distances using GoogleEarth® (Google Inc., 2015). When relying on participant-reported distances, one mile from a field was concluded as the cut-off point that made a significant difference between agricultural pesticide levels in house dust. However, after measuring the actual distances, <0.5 mile from a field was found to be the more precise cut-off point for influencing agricultural pesticide levels in household dust. This discrepancy in participant reported distances between home and nearest agricultural field when compared to the measured distances using GoogleEarth® (Google Inc., 2015) shows that some participants were not aware of how close they actually lived to an agricultural field. Another possible reason for the discrepancy could simply be the fact that distances can be difficult to judge for many people, which further highlights the advantage of using objective measures whenever possible.

Table 5-17: Studies that Assessed Association between Distance from Homes to Nearest Field and Agricultural Pesticide Levels in Homes

Study	**Distance**	**Findings**	**Conclusions About Pathways**
Simcox et al., 1995	Agricultural families <50 feet, 50-200 feet, and >200 feet vs. Reference families: >400 feet	Agricultural families had significantly higher concentrations of pesticides in house dust Pesticides still detected for reference families, but many reference families lived within 0.5 mile (2,640 feet)	Distance to spray areas is predominant factor for elevated pesticides in house dust; track-in may also contribute
Loewenherz et al., 1997	Agricultural children ≤ 200 feet of orchard vs. “Agricultural children” >200 feet of orchard vs. “Reference children” >200 feet from orchard	Pesticide levels higher in agricultural children than in reference children Children living ≤200 feet from orchard associated with higher detection frequency compared to children >200 feet	Although children living closer to orchard associated with greater exposure; no conclusions made whether distance was the primary determinant of children’s exposure
McCauley et al., 2001	Migrant camps and other farmworker houses up to 920 meters from field	Median pesticide levels decreased 18% when distance doubled	Associations between distance and pesticide levels driven by a few outliers; no conclusion about transport pathways
Richards et al., 2001	Homes 73-110 meters from field, sampling, within 5 meters of the home, 30 meters from home, and at edge of the field	Pesticide vapor detected adjacent to home, but not where wind was blowing away from the home, except at the edge of the field; no pesticide vapor detected inside homes	Individuals living adjacent to fields aerially sprayed with pesticide potentially exposed to vapors; wind speed and direction most important factors

Table 5-17: Studies that Assessed Association between Distance from Homes to Nearest Field and Agricultural Pesticide Levels in Homes (continued)

Study	**Distance**	**Findings**	**Conclusions About Pathways**
Curl et al., 2002	Distance from field: < 1 block, 1–2 blocks, 2–4 blocks, 4–8 blocks, 8 blocks–1 mile, > 1 mile	Pesticide levels in house dust and child's urine not significantly associated with proximity to fields	Possibly no differences because sampling in region not conducive to wind patterns that would lead to air transport compared to other regions
Lu et al., 2000; Fenske et al., 2002	Agricultural families <50 feet, 50-200 feet, 200-400 feet, >400 feet vs. Reference families >400 feet	Some pesticides significantly higher in the house dust of agricultural families	Suggests take-home pathway
McCauley et al., 2003	Agricultural families: 14-4,752 feet (median= 239 feet) vs. reference families: 1,100-2,640 feet (median=1,884 feet)	No association between distance to nearest active orchard and OP levels	Suggests take-home pathway; distance uncertain because most homes very close to field, so very little variability
Quandt et al., 2004	Adjacent homes: next to, across road from, or within short walk from fields vs. Nonadjacent homes: in areas with no fields	Elevated risk of agricultural pesticides given agricultural fields adjacent to the house	Homes next to fields may be contaminated by drift application, along with wind circulation of dust from fields
Ward et al., 2006	Distance from field: ≤750 meters ; >750 meters	No association between distance to treated land and pesticide levels; herbicides increased for each 10-acre increase of crop acreage up to 750 meters	Both take-home and drift pathways could contribute

Table 5-17: Studies that Assessed Association between Distance from Homes to Nearest Field and Agricultural Pesticide Levels in Homes (continued)

Study	**Distance**	**Findings**	**Conclusions About Pathways**
Curwin et al., 2005	Distance from field: <0.25 mile; 0.25 – 0.50 mile; 0.50-0.75 mile; 0.75-1.00 mile; >1.00 mile	Pesticide levels not correlated with distance of pesticide-treated fields to non-farm homes, analysis not performed for homes because all <0.25 mile from field	Possible contributions of take-home pathway and spray drift
Weppner et al., 2006	15-200 meters of nearest treated field	Pesticide residues found on deposition plates, playground equipment, toys, and children's' hands; distance and loading inversely associated; residues within treated fields 3 orders of magnitude higher than outside treated area	Drift occurred following aerial application; possible that presence of field investigation staff influenced well-performed application (targeted area much higher than outside targeted area)
Harnly et al., 2009	Distance from field: ≤60 meters. > 60 meters	Increased pesticide application up to 2,800 meters radius around home associated with increased pesticide dust concentrations; no differences seen between homes within and greater than 60 meters of field	Suggests a combination of nearby agricultural applications drift and take-home
Coronado et al., 2011	Distance from field: <200 feet, 200 feet-<0.5 mile, 0.5 mile-1 mile, >1 mile	No association between distance and pesticide levels in house dust, living further associated with 20% reduction per mile of pesticide metabolites in urine	Some drift may have occurred but likely to be less than other studies because used air blast sprayers rather than aerial application; not very conclusive because no association with house dust

Table 5-17: Studies that Assessed Association between Distance from Homes to Nearest Field and Agricultural Pesticide Levels in Homes (continued)

Study	**Distance**	**Findings**	**Conclusions About Pathways**
Gunier et al., 2011	≤500 meters and ≤1, 250 meters	Higher concentrations in house dust of some pesticides applied within 1,250 meters of home during the prior year compared to homes that did not have applications nearby	Drift occurs beyond 500 meters of treated fields
Golla et al., 2012	≤75 feet, 76-199 feet, ≥200 feet	No association between distance and atrazine in dust for planting and non-planting seasons	Levels could be from take-home pathway but study was not able to assess this
Lozier et al., 2012	"Reasonable driving distance from laboratory"; actual distances not specified	No association between distance from home to field and atrazine in dust	Suggests take-home pathway
Deziel et al., 2013	≤1,250 meters	Application of trifluralin within 1,250 meters of home significantly associated with levels in dust; association not observed for 8 other pesticides	No conclusions made about transport pathways

5.4.4 Importance of Cleaning and Maintaining the Homes

In the current study, factors related to the overall cleanliness of the home (i.e., cleaning the house frequently and not allowing the house to be visibly dusty) were more associated with reduced agricultural pesticide levels in homes than methods of cleaning the floors (i.e., cleaning the floors frequently, using only wet methods to clean floors) in particular for both bifenthrin and permethrin. In fact, the association between most recent house cleaning and decreased permethrin in the house dust was a significant finding ($p=0.02$). This may imply that a full house cleaning, which is likely to be a more thorough practice, is more effective than simply cleaning the floors, which is often associated with quick and light maintenance. Previously, cleaning the home was associated with reducing pesticide levels in the house dust in McCauley et al. (2003) and McCauley et al. (2006). On the other hand, some studies did not find an association between cleaning the home and pesticide levels in the house dust (Simcox et al., 1995; Fenske et al., 2002; Curwin et al., 2005; Coronado et al., 2012). One possible reason why some studies showed effectiveness in cleaning, and other did not, could be based on how easy it is to clean the homes. Both Quandt et al. (2004) and Harnly et al. (2009) reported a positive association between homes categorized as "difficult to clean" and pesticides in the house dust.

It also possible that it is more difficult to remove pesticides from the floor, especially when there is carpet, since this is a well-established reservoir for contaminants (Lewis et al., 1994; Wolz et al., 1994; Simcox et al., 1995). The positive association between having carpet in the house and levels of bifenthrin in house dust ($p=0.09$) may be a reflection of homes that cannot as easily remove pesticides from their floors through the cleaning processes. Prior research has established that mechanical cleaning processes are often highly ineffective at removing semi-volatile organic compounds from carpet fibers and the foam pad underlying the carpet, and that replacing the material was necessary to completely remove the compounds (Lu et al., 2000; Hunt et al., 2008; Shin et al., 2013). In the current study, the house dust sample was not necessarily taken from carpet, and in some cases, the sample included dust from furniture or curtains in order to gain enough mass for a dust sample. Therefore, the association between bifenthrin in the house dust and having carpet should be considered more of an additional proxy of how easily families can effectively clean their homes to remove pesticides rather than a direct association of pesticide levels by floor type.

Interestingly, the effect of having carpet in the house was not influential on permethrin levels in house dust. This is surprising because permethrin, in particular, is often incorporated into carpets at manufacturing facilities to prevent insecticide damage and it is known to adsorb well into the carpet (Leng et al., 1997, Schettgen et al., 2002). Since permethrin is a common residential pesticide used to combat insecticides in the home, it is possible that families who had carpet were less inclined to spray residential pesticides in their home due to notion that one cannot easily wash carpet, compared to a hard surface, after being sprayed with a pesticide. Another possibility is that families with children may be more likely to have carpet in their home since this type of flooring is generally considered to be more “child friendly” and that these homes are more difficult to keep clean.

Although advising farmworker families to remove carpet from their homes could be a sound recommendation to make the house easier to clean and potentially reduce agricultural pesticide levels in the home, it may not be practical to actually implement this, particularly in low-income households. Nonetheless, it is recommended that, in the future, homes in agricultural communities install hard floors rather than carpet.

5.4.5 Consistently Less Influential Factors for Bifenthrin and Permethrin

Multiple factors were consistently less influential on the levels of both bifenthrin and permethrin in the sampled house dust. First, correlations between household pets and levels of bifenthrin and permethrin in the house dust were weak. This finding matches that of Simcox et al., (1995), McCauley et al., (2003), Curwin et al., (2005), and Lozier et al., (2012) who each found no association between the presence of pets and pesticide levels in the dust. However other studies did find an association between having a dog and levels of pesticides in the house dust (Morgan et al., 2001; Nishioka et al., 2001b; Golla et al., 2012; Deziel et al., 2013). However, in the current study, the majority of families kept their pets outdoors, and thus there was insufficient variability to truly assess the effect of having indoor pets or pets that moved between indoors and outdoors.

Adjusting each type of household resident by square footage of the house generally weakened the correlations with pesticide levels in the house dust for both bifenthrin and permethrin. This was an interesting finding because the number of household residents in the current study is approximately double (4.38 people) compared to that of the general United States' population (2.63 people) (US Census, 2015a), while the median square footage in the current study (1,040 ft^2) was about half that of overall homes in the United States (2,494 ft^2) (US Census, 2015b), meaning that the density of residents in the sampled homes is about four times that of the general population. Nonetheless, the negative correlation matches the results of previous studies that reported no association between people per square footage among farmworkers (McCauley et al., 2001), as well as among agricultural owners or managers (McCauley et al., 2003). One possible explanation for why the actual number of people, children, and farmworkers were each much more influential before square footage adjustments than after is the fact that families living in bigger residence may only actively use a portion of their homes. For example, some families may have a spare bedroom that largely remains unoccupied and thus, does not contribute actively to the distribution of pesticides in the house dust. Another possible reason why square footage adjustments were weak could be due to a lack of variability in square footage of homes in this study. The fact that most homes in this study were quite small may contribute to the lack of effect observed when square footage adjustments were made. Although the sampled homes ranged from ~300-3,000 ft^2, they were mostly considered to be small (median=1,040 ft^2) compared to overall homes in the United States in 2013 (2,494 ft^2) (US Census, 2015b). Only two homes in this study were at least the same size as the United States' median square footage.

Finally, for both bifenthrin and permethrin, frequency and type of heating and cooling were less influential factors on house dust levels. It is possible that a relationship exists between the more influential findings of this study, such as opening doors/windows and changing air filters, with heating and cooling, but the methods used in the current study were not able to capture such effects. In Chapter 6 of this dissertation, heating and cooling is found to be influential on permethrin levels when an alternative statistical method; please see that Chapter for further information. Future researchers may want to more specifically design their questionnaires to look closely at these factors as they may provide insight to household behaviors that promote air infiltration.

5.4.6 Conclusions

In the current Chapter, the author successfully identified various household-level risk factors that are associated with agricultural pesticide levels at the farmworkers' homes, partially fulfilling the third major aim of this dissertation. The findings of this Chapter highlight the strong influence of agricultural pesticide applications on pesticides in the house dust of farmworkers' homes, and suggest that living near an agricultural field may more influential on pesticide levels in the dust than farmworker status. Also, household-level risk factors related to the entire household were found to be more influential than factors that were limited to only the farmworkers themselves. Classic farmworker behaviors thought to be related to the take-home pathway, such as removing shoes before entering the home and changing clothes and showering right away after work were not found to influence pesticide levels in the house dust. Rather, factors related to the entire household, such as distance to the nearest agricultural field, square footage of the home, having door mats, frequency of changing air filters, and the number of total people in the home were more strongly associated with pesticide levels in the house dust. For permethrin, there is likely a residential usage component in addition to agricultural use. For both bifenthrin and permethrin, the ability to effectively clean the home may play a key role in removing pesticides from the home.

CHAPTER 6

USING CLASSIFICATION AND REGRESSION TREE (CART) MODELS TO IDENTIFY MODIFIABLE AND NON-MODIFIABLE HOUSEHOLD-LEVEL RISK FACTORS THAT INFLUENCE AGRICULTURAL PESTICIDE TRANSPORT INTO FARMWORKERS' HOMES VIA AIR INFILTRATION AND SOIL TRACK-IN PATHWAYS

6.1 Introduction

6.1.1. Household-Level Risk Factors and Agricultural Pesticide Transport into Farmworkers' Homes

The quest to understand pesticide transport away from agricultural fields and into farmworkers' homes is a complicated matter because of the many potential factors that may affect this transport, along with the interaction these factors may have with each other. It is currently not well understood which factors at the household-level most strongly affect agricultural pesticide transport into homes. It is also unknown whether household level efforts could be rendered ineffective after a certain threshold level of nearby agricultural pesticide applications is reached.

If agricultural pesticides entering the home are indeed influenced by household-level risk factors, it is worth exploring whether these factors are easily modifiable factors that families could control through changes in household behaviors. Given that the farmworkers in the current study are part of a low-income population that works long hours, factors that are part of the built structure of the house and would require expensive, time-consuming, or resource-intensive modifications were considered to be non-modifiable. In the previous studies that assessed association between agricultural pesticides in farmworkers' house dust with household-level factors, many of the identified factors that would considered as not feasibly modifiable included: distance to nearest agricultural field (Simcox et al., 1995; Loewenherz et al., 1997; McCauley et al., 2001; Quandt et al., 2004; Weppner et al., 2006; Harnly et al., 2009; Coronado et al., 2011; Gunier et al., 2011; Deziel et al., 2013), square footage of the home (McCauley et al., 2003), and having carpet in the house (Lu et al., 2000; Hunt et al., 2008; Shin et al., 2013). In Chapter 5 of this dissertation, the author explored a broad range of household-level factors and assessed the association of each one with the presence of agricultural pesticides in the house dust of farmworkers' homes. In that Chapter, a combination of modifiable factors (e.g., not have mats outside of doors, cleaning the house infrequently) and non-modifiable factors (e.g., having more residents and farmworkers in the house, being close to an agricultural field) were identified as positively associated with agricultural pesticide levels in the house dust. Previous identification of influential household-level factors on agricultural pesticide levels in the house dust has been beneficial first steps to providing insight about the pathways of agricultural pesticide transport. For example, distance between home and nearest agricultural field offers evidence of the air infiltration pathway. However, in the previous studies mentioned and in the current author's work outlined in Chapter 5, only univariate analyses were performed, in which each single risk factor was tested for association with agricultural pesticide levels in the house dust, thereby limiting the ability to examine how identified risk factors interact with each other. Since household-level factors may interact with each other, it is crucial to consider these factors together through multivariate analyses.

The current Chapter seeks to expand upon the findings of the Chapter 5 and continues to address the third major aim of this dissertation, which was to identify relevant household-level risk factors for increased in-home agricultural pesticide levels. This current Chapter uses a multi-variate approach to assessing the influence of various household-level risk factors on agricultural pesticide detection frequency in outdoor air, yard soil, and house dust of farmworkers' homes by building a series of classification and regression tree (CART) models, a type of decision tree classification analysis. The hypothesis associated with the third major aim is that most of the household-risk factors associated with in-home agricultural pesticide levels are housing structure characteristics related to the air infiltration pathway, and that these factors will not be easily modifiable at the household-level.

6.1.2 Decision Tree Classification: A Useful Multivariate Statistical Method

One highly effective, although less commonly utilized, multivariate statistical method that can be used to explore the influence of multiple factors on a dependent variable is called "decision tree classification." Decision tree classification develops a tree-based model through the process of identifying predictors on an outcome, with the intention of these predictors being generalizable beyond the specific dataset at hand. Please note that the term "factor" is simply a more general term, while "predictor" is usually the term used for factors considered for statistical purposes. As such, "factor" and "predictor" are henceforth used interchangeably. The decision tree classification methodology, also known as recursive partitioning, uses an algorithm to recursively partition, or split, a set of data until each observation within the dataset belongs to an identified class (Yohannes and Webb, 1999). The algorithm behind the recursive partitioning of the data can vary based on the philosophy of splitting data chosen by the user, commonly referred to as a “splitting rule.” Among the most popular “splitting rules” are: Gini criterion, linear combination splits, and twoing rule (Yohannes and Webb, 1999; Breiman et al., 1984). The Gini criterion splits data based on the largest single class within a single variable in the database, while the linear combination splits finds the largest single class using a combination of variables (Yohannes and Webb, 1999). The twoing rule, alternatively, splits based on classes that comprise 50% of the data (Breiman et al., 1984). When a designated “stopping rule” is achieved, which occurs when there is less than a designated sample size available to split, splitting is ceased. Note that when the “stopping rule” is reached prior to a single split (i.e., there was no factor in which the data could be split with at least 5 observations in both nodes), then the minimum splitting requirement would be considered unmet, and no tree would be grown.

The structure of the general decision tree model begins with an initial split, called a root, which includes the total sample set. This first split is the most important predictor. The data continues to split in the internal nodes, each which include a subset of the sample belonging to an identified class. When no further splitting occurred because the “stopping rule” was reached, the nodes became terminal (Figure 6-1).

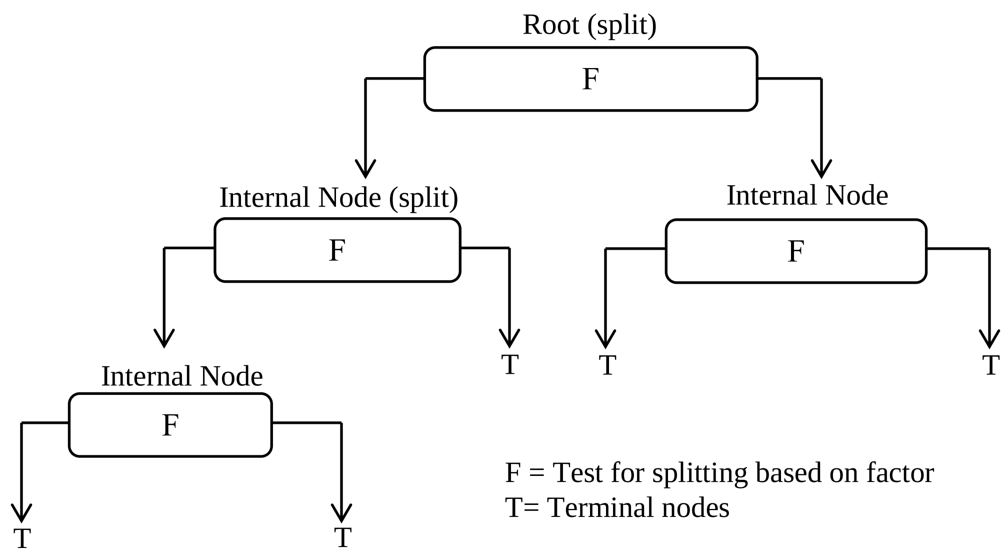


Figure 6-1: Structure of Decision Tree Model (Adapted from Yohannes and Webb, 1999)

6.1.3 Classification and Regression Tree (CART) Analysis

Classification and Regression Tree (CART) analysis is a specific type of decision tree classification that performs binary recursive partitioning. CART models have internal nodes with exactly two outgoing branches based on whether the condition within the node is met or not met, unlike alternative decision tree models that may include more than two branches per node (Breinman et al., 1984; Venkatadri and Reddy, 2010). Two types of tree-based models may be grown through CART: a classification tree that has a categorical outcome variable; or a regression tree that has a continuous outcome variable. CART models assume the gini splitting criterion to grow trees continues until the designated “stopping rule” is met.

Complex trees (complexity is measured by the number of terminal nodes of that tree) run the risk of over-fitting the data, and as such pruning the tree back is often necessary. Pruning of the tree is most frequently done through 10-fold cross-validation, which is a method of self-testing the model for reliability and generalizability (Yohannes & Webb 1999; Lemon et al., 2003). 10-fold cross validation consists of splitting the overall sample into 10 equally sized subsets. For each of the 10 folds, the analysis is performed on all subsets except one, which is used to validate the model and evaluate the error within the data being tested. This process is repeated 10 times, each time leaving a different subset out. The errors for the 10 validations are averaged which is referred to as the "*xerror*." At each pair of nodes, it is tested whether the variance of the data would decrease if those nodes were removed, and if this is found to be true, the tree is pruned back by removing the nodes. Since there is a trade-off cost between accuracy of classification and complexity of the tree, cross-validation is based on the concept of cost-complexity in which there is a penalizing cost for each unit increase of complexity (i.e., one more terminal node). This value is referred to as the "complexity parameter" (CP). The CP value associated with the minimum cross-validated misclassification error (*xerror*) is used to optimally prune the tree and the final CART model will have an ideal balance between classification accuracy and complexity (ibid).

CART is a very powerful tool in that it is able to overcome many of the limitations of traditional statistical methodologies used for predictive modeling. Perhaps the most popular of these traditional statistical approaches are multiple linear regression, which is used for continuous outcomes (Allison, 1999) and multiple logistic regression, which is used for categorical outcomes (Agresti et al., 2007). Similar to CART models, multiple linear/logistic regressions allow multiple factors to be combined to make predictions about an outcome of interest, and can separate the effects of each independent factor, allowing the relative contribution of each factor to emerge. However, multiple linear/logistic regression analyses are limited by several conditions. First, multiple linear regression and multiple logistic regression are both based on a linear equation, thereby assuming that the relationship between the independent predictors and dependent outcome is linear. If, however, in reality the nature of this relationship is not linear, the regression may not reveal reasonable predictions (Allison, 1999; Agresti et al., 2007). In the case of CART, there is no underlying assumption of a linear relationship, allowing other, more complex, relationships to become known. Second, it is well established that a larger sample size improves the accuracy of multiple linear/logistic regression analyses, yet the minimum number of samples needed per predictor variable has always been highly debated. Previously, some have put forth a “rule of thumb”, ranging from 10 samples per predictor variable (Miller and Kunce, 1973; Agresti, 2007) to 30 samples per predictor variable (Pedhazur and Schmelkin, 1991), while others have suggested more sophisticated methods to determine the necessary sample size, such as incorporating effect size (Green, 1991) or using correlations between the outcome variable and predictor variables (Knofczynski, 2007). For CART models, it is not necessary to choose predictor variables ahead of time or to limit the number of included predictors based on sample size. Rather, all potentially influential factors can be included and the CART algorithm will identify the most important predictors and remove the unimportant one automatically (Timofeev, 2004). Finally, multiple linear/logistic regression analyses are parametric tests, meaning they assume that underlying distributions of all factors are normal. As such, any non-normal factors would need to be transformed into a normal distribution, or it is otherwise eliminated from the analysis (Osborne & Waters, 2002). CART analysis, on the other hand, is a non-parametric test and therefore, does not require normal distributions; in fact, transformations will not change the structure of the tree at all (Timofeev, 2004).

Of course it should also be noted that CART modeling has certain limitations. First, it is possible for CART to grow an unstable tree where a small change to the data could result in the building of a completely different tree (Timofeev, 2004; Prasad et al., 2006). This is particularly true when the predicted outcomes are categorical (i.e., classification trees) because small changes in the predictors can completely change the classification. Another limitation of CART analysis is that it is coarse-grained, which means that the number of predicted possibilities cannot be more than the number of nodes produced. From this perspective, a small sample is less favorable since it limits the number of nodes, and thus, the growing of trees. Finally, with some datasets, it is not always possible to select the optimal complexity parameter (CP) through cross-validation, compromising the classification accuracy and reliability of the model (ibid). A final limitation of CART is that it does not necessarily identify predictors, and designate splits that yield a statistically significant difference in the outcome variable by the designated split of the predictor variable. Therefore, caution should be used in making conclusions regarding the CART splits, and it is recommended that further statistical tests be used to determine whether the split of the predictor variable yields a statistically significant difference in the outcome variable.

6.1.4 Applications of CART

The application of CART models has been slowly on the rise in the health sciences field, such as for exploration of risk factors for morbidity and mortality from diseases (Nelson et al., 1998; Choi et al., 1991; Bachur and Harper 2001; Camp & Slattery 2002) and development of diagnostic and screening procedures (LaValley et al., 2001; Lemon et al., 2003). Within environmental health, in particular, CART models have been largely used to explore the effect of exposures, especially mixtures, on health outcomes (Roy et al., 2003; Sun et al., 2013; Gass et al., 2014; Lampa et al., 2014). There has been a study in which CART models were built to determine which housing characteristics were most strongly associated with pesticide levels in homes, but this was done from the perspective of residential pesticide use (Julien et al., 2008). The current study in this dissertation sought to apply a novel application of CART modeling by identifying household-level risk factors associated with agricultural pesticides, an outdoor contaminant, on detection frequency of pesticides in residential outdoor air, yard soil, and indoor house dust.

6.2 Methods

6.2.1 Conceptual Design of CART Models

Classification and regression tree (CART) analysis was used to explore which household-level factors from the questionnaire are most predictive of pesticide detection frequency in the outdoor soil and air, along with indoor house dust while taking into consideration multi-level interactions. For the current study, the specific type of CART models built were “classification trees”, which had a binary outcome variable of “non-detect” and “detect” in outdoor soil, outdoor air, and indoor house dust. Although the sampling portion of this study consisted of analyzing samples for several pesticides, only bifenthrin and permethrin had a detection frequency of at least 30% in at least one media type, and therefore, only these two pesticides were used for the CART analysis.

A series of CART models were developed based on the goals of identifying influential predictors for: 1) pesticide detection frequency in outdoor soil and air, and indoor house dust 2) pathways of pesticides into the house (i.e., air infiltration and soil track-in) with and without agricultural applications nearby taken into consideration, and 3) household-level factors are that are feasibly modifiable through behavioral changes or non-modifiable because they are part of the built structure of the house and would require substantial time, finances, and resources to make changes.

A total of 7 CART models were generated for each pesticide. See Figure 6-2 for a causal diagram of the 7 CART models used to identify influential factors on pesticide detection frequency in the outdoor soil and air and indoor house dust. CART 1 and CART 2 were used to assess factors that may potentially influence pesticide detection frequency in outdoor soil and air, respectively. These factors included the influence of nearby agricultural applications of the pesticide, as well as factors at the household-level that could influence detection frequency in the outdoor media (Table 6-1).

The remaining CART models 3-7 each explored factors that could influence pesticide detection frequency in house dust. CART 3 focused on factors related to the air infiltration pathway (Table 6-2) and CART 4 focused on factors related to the soil track-in pathway (Table 6-3). In order to identify both the level of influence of nearby agricultural applications of pesticides and household-level factors that may promote or prevent the pesticide from entering the home, CART 3 and CART 4 were each performed twice so that CART 3A/CART 4A included nearby agricultural pesticide applications and CART 3B/4B did not include nearby agricultural pesticide applications.

Next, CART 5 focused on factors that would be feasibly modifiable by the household (Table 6-4) and CART 6 focused on factors that would not be modifiable because they are related to the housing structure or the intrinsic demographics of the household (Table 6-5). Finally, all factors from the previous CART models were combined to consider all potentially influential factors together and elucidate which factor(s) was/were overall most influential on pesticide detection frequency in house dust taking into account nearby agricultural applications of pesticides (CART 7A) and without taking into account nearby agricultural applications (CART 7B).

Table 6-1: Factors Considered for Pesticide Detection Frequency in Outdoor Air (CART 1) and Outdoor Soil (CART 2)

Potentially Influential Factors	**Variable Type**	**Variable Range/Categories**	
Number of people, farmworkers, children, outdoor pets (solely and partially)	Continuous	0-9	
Percentage of yard coverage	Continuous	0-100	
Residential pesticide use[+]	Categorical	No/Yes	
Pesticide detection in outdoor soil/outdoor air (used opposite of outcome variable)	Categorical	Non-Detect/Detect	
Measured distance to nearest agricultural field (ft)	Continuous	50-4,427	
Agricultural Pesticide application (lbs):	Continuous	*Bifenthrin:*	*Permethrin*:
• within 1-mile of home and 1-month prior to sampling		0-24	0-25
• within 1-mile of home and 1-year prior to sampling		0-134	0-73
• throughout Yuma County 1-month prior to sampling		726-4,819	5,817-13,152
• throughout Yuma County 1-year prior to sampling		20,672-44,547	2,797-61,281

[+] residential pesticide use only included for permethrin CART model because only permethrin used by participants, as reported in the questionnaire

Table 6-2: Factors Considered for Pesticide Detection Frequency in House Dust via Air Infiltration Pathway (CART 3A/3B)

Potentially Influential Factors	**Variable Type**	**Variable Range/Categories**	
Number of window panes	Categorical	Single/Binary	
Frequency of opening doors and windows	Ordinal	Never/Once a month/Once a week/ Everyday	
Months of heating	Continuous	0-8	
Months of cooling	Continuous	3-8	
Type of heating	Categorical	No heating/Central heating/Space heater or other	
Type of cooling	Categorical	Central air conditioning/Window air conditioning	
Frequency of changing air filters (times/year)	Continuous	1-104	
House at least 10 years old	Categorical	No/Yes	
Square footage of the home (ft^2)	Continuous	311-3,224	
Distance to nearest agricultural field (ft)	Continuous	50-4,427	
Pesticide detection in outdoor air	Categorical	Non-detect/Detect	
Residential pesticide use	Categorical	No/Yes	
Agricultural Pesticide application (lbs):	Continuous	*Bifenthrin:*	*Permethrin:*
• within 1-mile of home and 1-month prior to sampling		0-24	0-25
• within 1-mile of home and 1-year prior to sampling		0-134	0-73
• throughout Yuma County 1-month prior to sampling		726-4,819	5,817-13,152
• throughout Yuma County 1-year prior to sampling		20,672-44,547	2,797-61,281

Table 6-3: Factors Considered for Pesticide Detection Frequency in House Dust via Soil Track-in Pathway (CART 4A/4B)

Potentially Influential Factors	**Variable Type**	**Reported Range/Categories**	
Number of people, children, farmworkers, and pets	Continuous	0-9	
Number of people, children, farmworkers, and pets per 1,000 ft^2 of home	Continuous	0-19	
Time until farmworkers remove shoes, change clothes, and shower (each one asked separately)	Ordinal	Before arriving home/Right away upon arriving home/Several hours after arriving home/Right before bed	
Carpet in home	Categorical	No/Yes	
Frequency of floor cleaning	Ordinal	Once a week or less/Several times a week/Everyday	
Whether or not dry methods used to clean the floor	Categorical	No/Yes	
Frequency of house cleaning	Ordinal	Once a week or less/Several times a week/Everyday	
Square footage of home (ft^2)	Continuous	311-3,224	
Percentage of yard coverage	Continuous	0-100	
Doors with outdoor mats	Ordinal	None/Some/All	
Doors with indoor mats	Ordinal	None/Some/All	
Distance to nearest agricultural field (ft)	Continuous	50-4,427	
Pesticide detection in outdoor soil	Categorical	Non-detect/Detect	
Pesticide detection in outdoor air	Categorical	Non-detect/Detect	
Agricultural Pesticide application (lbs):	Continuous	*Bifenthrin:*	*Permethrin:*
• within 1-mile of home and 1-month prior to sampling		0-24	0-25
• within 1-mile of home and 1-year prior to sampling		0-134	0-73
• throughout Yuma County 1-month prior to sampling		726-4,819	5,817-13,152
• throughout Yuma County 1-year prior to sampling		20,672-44,547	2,797-61,281

Table 6-4: Factors Considered for Pesticide Detection Frequency in House Dust via Modifiable Household Behaviors (CART 5)

Potentially Influential Factors	**Variable Type**	**Reported Range/Categories**
Time until farmworkers remove shoes, change clothes, and shower (each one asked separately)	Ordinal	Before arriving home/Right away upon arriving home/Several hours after arriving home/Right before bed
Frequency of floor cleaning	Ordinal	Once a week or less/Several times a week/Everyday
Frequency of house cleaning	Ordinal	Once a week or less/Several times a week/Everyday
Whether or not dry methods used to clean the floor	Categorical	No/Yes
Frequency of opening doors and windows	Ordinal	Never/Once or twice a month/Once or twice a week/Everyday
Months of heating	Continuous	0-8
Months of cooling	Continuous	3-8
Frequency of changing air filters	Continuous	1-104
Residential pesticide use[+]	Categorical	No/Yes
Doors with outdoor mats	Ordinal	None/Some/All
Doors with indoor mats	Ordinal	None/Some/All

[+] residential pesticide use only included for permethrin CART model because only permethrin used by participants, as reported in the questionnaire

Table 6-5: Factors Considered for Pesticide Detection Frequency in House Dust via Non-Modifiable House Structure Characteristics Factors (CART 6)

Potentially Influential Factors	**Variable Type**	**Reported Range/Categories**
Carpet in home	Categorical	No/Yes
Percentage of yard coverage	Continuous	0-100
Type of heating	Categorical	No heating/ Central heating/ Space heater or other
Type of cooling	Categorical	Central air conditioning/ Window air conditioning
Distance to nearest agricultural field (ft)	Continuous	50-4,427
Number of window panes	Categorical	Single/Binary
House at least 10 years old	Categorical	No/Yes
Square footage of the home (ft^2)	Continuous	311-3,224

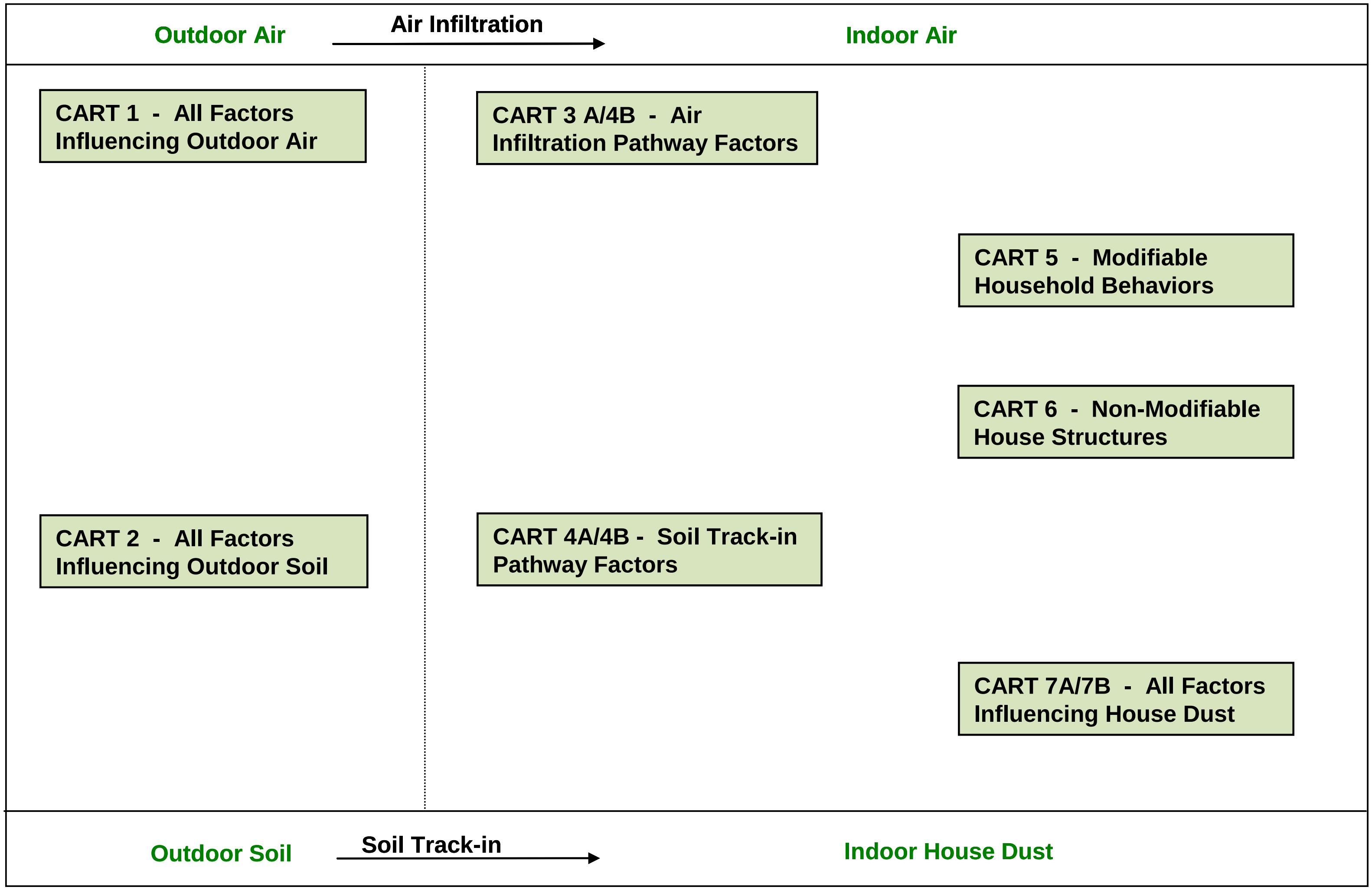


Figure 6-2: Causal Diagram of 7 CART Models Used to Identify Influential Factors on Pesticide Detection Frequency in Outdoor Soil and Air and Indoor House Dust

6.2.2 Execution of CART Analyses

The CART analyses were performed in RStudio (R Core Team, 2015), using the *rpart* package to grow each classification tree model. The gini splitting criterion was applied, which is the methodology of splitting based on the largest single class in the database. Note that when the minimum requirement of being able to split the data at least once with a resultant sample size of five or more in the nodes was not met, a tree could not be grown. The tree was grown (i.e., data continued to split) until the "stopping rule" of a sample size in all of the nodes being less than five was achieved. It should be noted that although a common "stopping rule" is a sample size less than 10, the lower limit of less than five was set for the current study due to the small starting sample size.

In order to determine if the grown out classification tree model had to be pruned back to avoid over-fitting the data, the cross-validated prediction error (CP value) for different numbers of splits were calculated. When the optimal CP value was associated with a model with at least one split, the tree was pruned back using this CP value. However, if the optimal CP value caused the tree to have no splits, then the next lowest listed CP value was used so that at model with at least one split could be built. Please see Appendix D for the complete code used in RStudio for execution of the CART analyses. To assess whether the splits determined by CART were statistically significant, Fisher's Exact tests were used in which the independent variable was based on the CART-determined split and the outcome variable was detect or non-detect in each media. An alpha level of 0.05 was considered for statistical significance.

The graphical representation of the pruned tree representing the final CART model can be seen in Figure 6-3. At the root, the identified influential factor is depicted based on the total sample size of farmworkers' homes and the initial pesticide detection frequency was reported based on the identified predictor. The significance level (p-value) from the Fisher's exact test that compared detection frequency between homes that met the condition of the influential factor versus those that did not meet the condition was also reported. Homes that did and did not meet the condition of the influential factor split the data into nodes to the left ("yes" response) and to the right ("no" response). The resultant nodes reported the sample size and the pesticide detection frequency within that split. This approach to interpretation would remain the same with further splits at internal nodes. When there are multiple splits, note that the first split is considered the most important predictor.

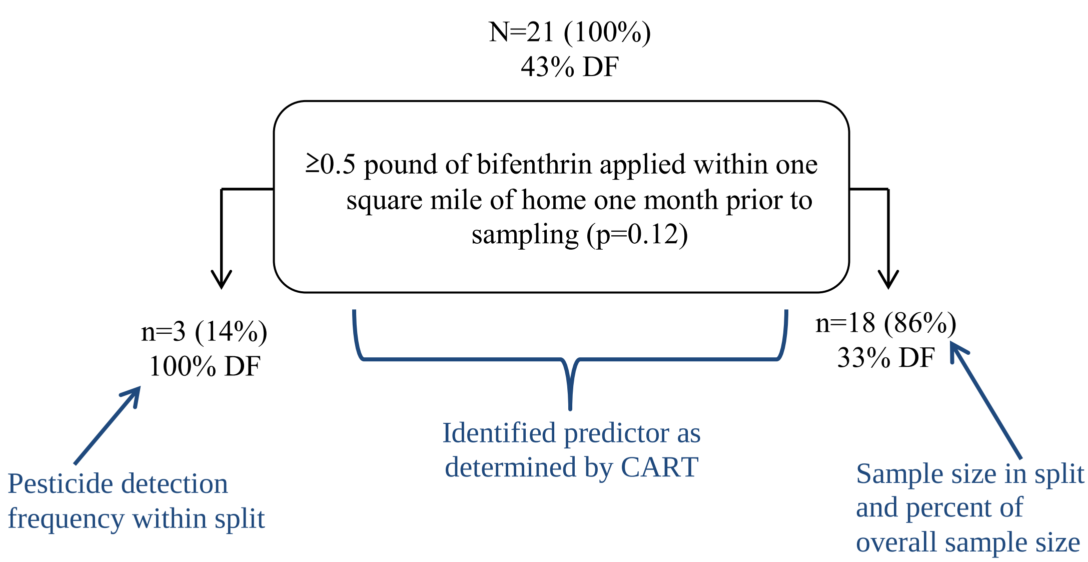


Figure 6-3: Example of Graphical Depiction and Interpretation of a Classification Tree

6.2.3 Assessing Effectiveness of CART Models

The effectiveness of each CART model was assessed from the following perspectives. The first perspective was based on whether the minimum requirement of being able to split the data at least once with a resultant sample size of at least five was met. If this was not met, the CART model was deemed to be "impossible" as no tree could be grown and "possible" if a tree could be grown. Please note that terminal nodes could have a sample size of less than five.

Next, for each CART model that could be grown, effectiveness was additionally assessed based on whether the optimal CP value was associated with a model containing at least one split. This was determined using the *printcp ( )* function in *rpart*, which lists the CP values alongside the cross-validation misclassification error rates (*xerror*); the optimal CP value was identified as the one with the lowest *xerror*. The *xerror* listed in this table is expressed as proportion of the root node error (RNE), which is the average deviance of the overall response variable data. If the optimal CP value could not be used to build a model with at least one split, an alternative CP value with a higher *xerror* was used, but it was noted that the CART model was "compromised." If the optimal CP value could be used, the CART model was considered "uncompromised."

In the third perspective to assess effectiveness of CART model, the misclassification rate (MCR) was computed to determine the percentage of misclassifications and the prediction accuracy (PA), which provides the overall accuracy of the CART model to make correct predictions, were computed using the following equations:

$$Equation\ 6 - 1: \ \ MCR = xerror \cdot RNE \cdot 100$$

$$Equation\ 6 - 2: \ \ PA = 100 - MCR$$

No guidelines for categorizing prediction accuracy could be found. Therefore, according to personal judgment the following cut-off points were used: a prediction accuracy of <50% rendered the model "unpredictive," 51-75% was considered "moderately predictive" and >75% was considered "highly predictive." Although the requirements to be "moderately predictive" or "highly predictive" may be considered low, based on the sample size of this study, these cut-off points were deemed to be appropriate and realistic.

6.3 Results

6.3.1 Bifenthrin CART Results

6.3.1.1 Potentially Influential Factors on Detection Frequency in Outdoor Air (CART 1)

For the bifenthrin CART 1 model (Figure 6-4) that assessed factors increasing detection of outdoor air levels of bifenthrin, there was a sole split at the root based on pounds of bifenthrin applied within one square mile circular buffer around the home one month prior to sampling. For homes with at least 0.50 pounds of application (n=3) the detection frequency in outdoor air was 100%, while for homes that did not meet this condition (n=18) the detection frequency in outdoor air was 33%. This split was not statistically significant (p=0.12).

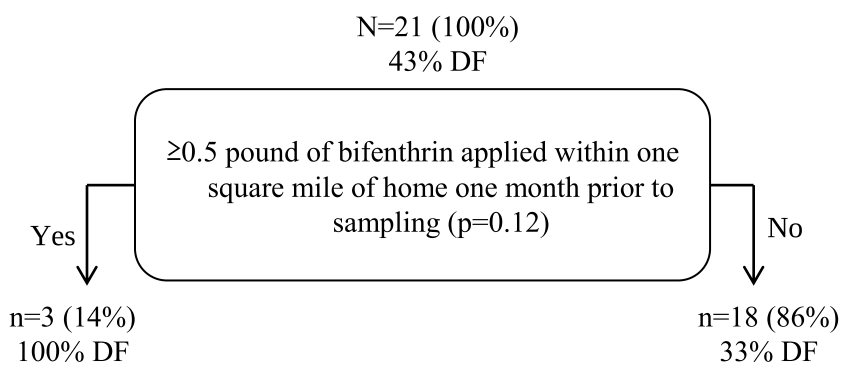


Figure 6-4: Classification Tree for Bifenthrin CART 1 Model- Factors Influencing Bifenthrin Detection Frequency in Outdoor Air

6.3.1.2 Potentially Influential Factors on Detection Frequency in Outdoor Soil (CART 2)

For the bifenthrin CART 2 model (Figure 6-5), which explored factors that could influence detection frequency in outdoor soil, a sole split based on number of pounds of bifenthrin applied throughout Yuma County one year prior to sampling was observed. For homes in which less than 22,000 pounds of bifenthrin were applied in Yuma County a year prior to sampling (n=9) detection frequency in the outdoor soil was 78%, while for homes where at least 22,000 pounds were applied (n=12) detection frequency was 8%. This was a statistically significant split (p=0.03).

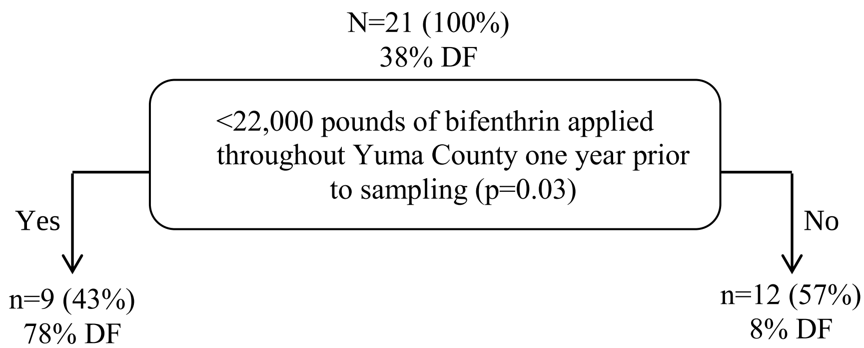


Figure 6-5: Classification Tree for Bifenthrin CART 2 Model- Factors Influencing Bifenthrin Detection Frequency in Outdoor Soil

6.3.1.3 Potentially Influential Air Infiltration Pathway Factors on Detection Frequency in House Dust (CART 3A and CART 3B)

For the bifenthrin CART 3A model, the only split occurred based on ≥77 pounds of bifenthrin applied per square mile within the past year (p=0.06) in which homes that met this condition (n=17) had a detection frequency of 83%, while homes that did not meet this condition (n=4) had a detection frequency of 33%.

For the bifenthrin CART 3B model, the first split occurred based on homes being <2,204 feet from nearest agricultural field (p= 0.09). For homes that met this condition (n=17) detection frequency was 59%, while for homes that did not meet this condition (n=4) detection frequency was 19%. The second split occurred based on the house being at least 695 ft^2. For homes that met this condition (n=14), detection frequency was 71%, while homes that did not meet this condition (n=3), detection frequency was 0%.

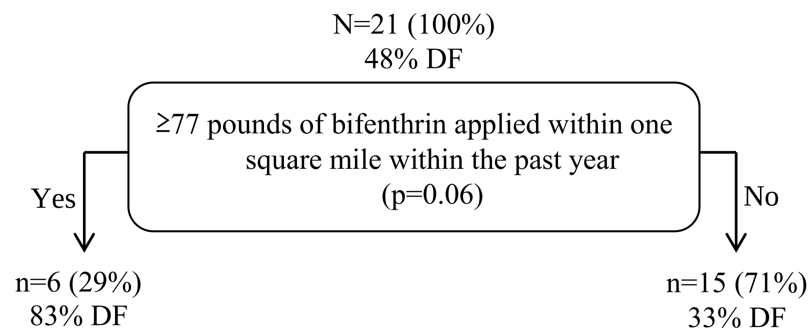


Figure 6-6: Classification Tree for Bifenthrin CART 3A Model - Air Infiltration Factors Influencing Bifenthrin Detection Frequency in House Dust *with* Agricultural Applications Considered

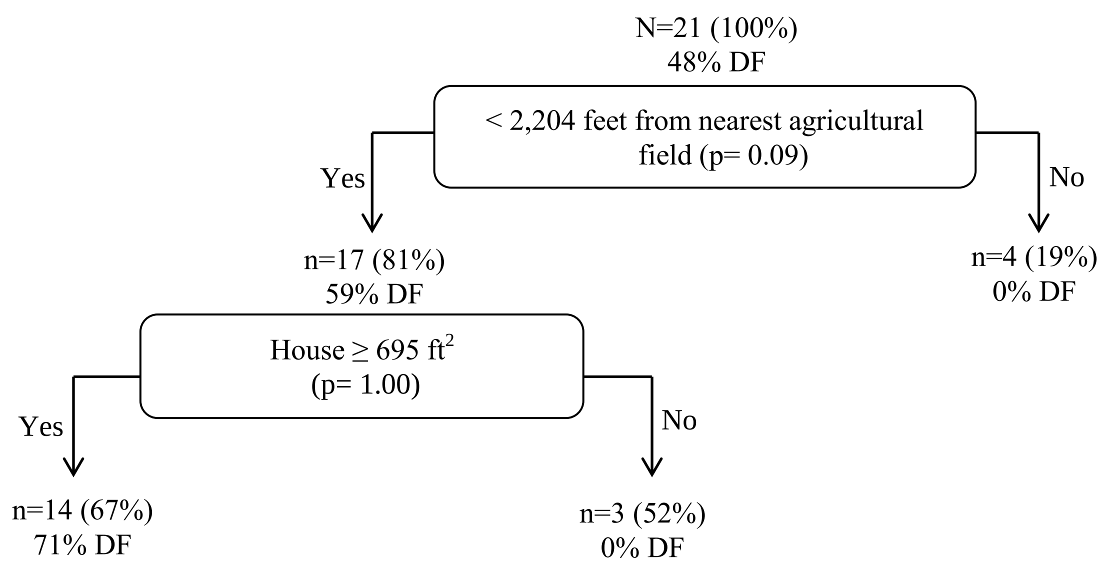


Figure 6-7: Classification Tree for Bifenthrin CART 3B Model - Air Infiltration Factors Influencing Bifenthrin Detection Frequency *without* Agricultural Applications Considered

6.3.1.4 Potentially Influential Soil Track-in Pathway Factors on Detection Frequency in House Dust (CART 4A and CART 4B)

For the bifenthrin CART 4A model, which explored soil track-in pathway factors with agricultural applications nearby considered, the only split was once again based on 77 pounds of bifenthrin applied per square mile within the past year ($p=0.06$) as was the case for the air infiltration factors in CART 3A.

For the bifenthrin CART 4B model, which explored soil track-in factors without considering nearby agricultural applications, the first split occurred based on ≥ 1 farmworker per 1,000 ft^2 ($p=0.09$). For those that met the condition ($n=13$) there was a detection frequency of 69% while those that did not meet the condition ($n=8$) had a detection frequency of 12%. A second split was based on homes less than 1,408 ft^2 ($p=1.00$) in which those that were smaller that this area ($n=11$) the detection frequency was 82%, while those that were not smaller than this area ($n=2$) the detection frequency was 0%.

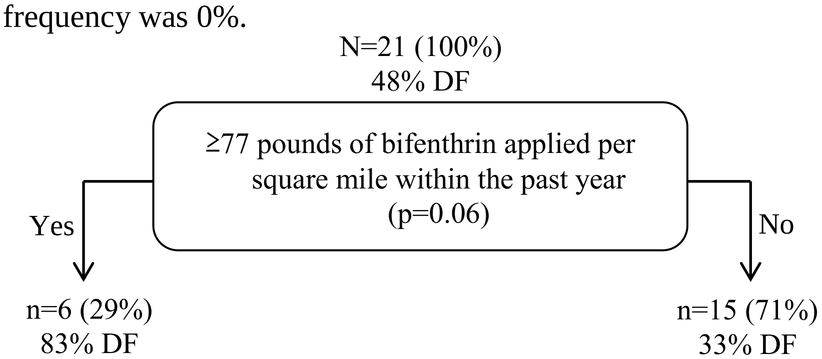
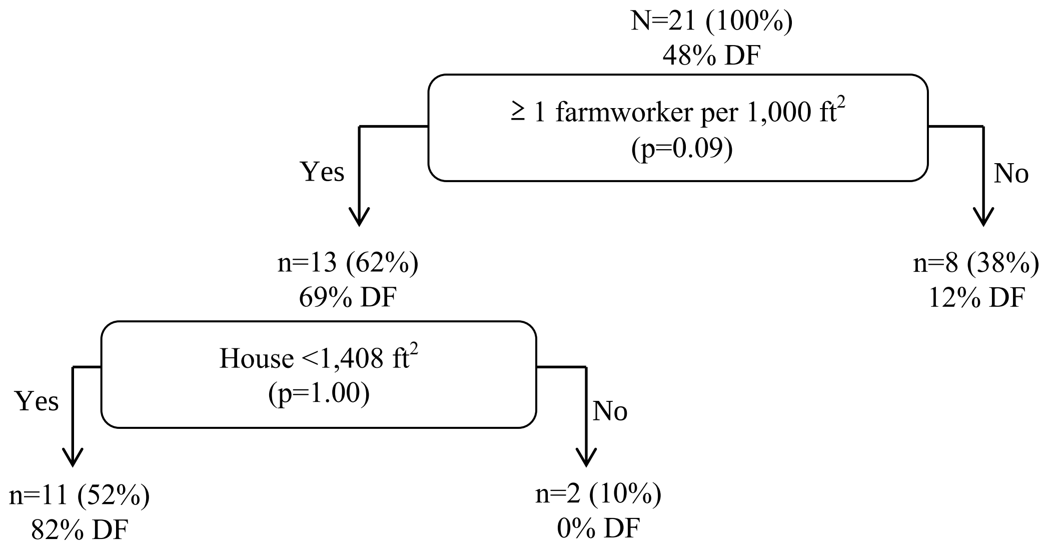


Figure 6-8: Classification Tree for Bifenthrin CART 4A Model - Soil Track-in Characteristics Influencing Bifenthrin Detection Frequency in House Dust *with* Agricultural Applications Considered



6-9: Classification Tree for Bifenthrin CART 4B Model - Soil Track-in Characteristics Influencing Bifenthrin Detection Frequency in House Dust *without* Agricultural Applications Considered

6.3.1.5 Modifiable Household Behaviors on Detection Frequency in House Dust (CART 5)

For the bifenthrin CART 5 model (Figure 6-10), which assessed factors influencing detection frequency in house dust with respect to household behaviors, the only split was based on time until farmworkers removed shoes. For homes where the farmworkers removed their shoes earlier (before arriving home or right away upon arriving home) (n=16) the detection frequency in house dust was 67%, while in homes where the farmworkers removed their shoes later (several hours after being home or just before bed) (n=5) the detection frequency in house dust was 0%. This split was statistically significant (p=0.01).

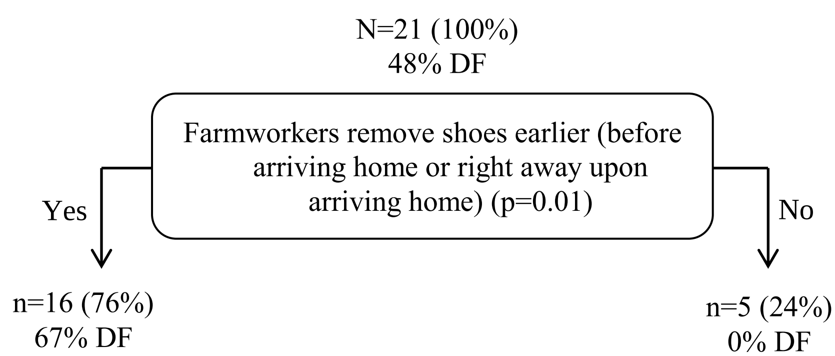


Figure 6-10: Classification Tree for Bifenthrin CART 5 Model - Modifiable Household Behaviors Influencing Bifenthrin Detection Frequency in House Dust

6.3.1.6 Non-Modifiable House Structures on Detection Frequency in House Dust (CART 6)

For the bifenthrin CART 6 model (Figure 6-11), which assessed factors influencing detection frequency of bifenthrin in house dust with respect to non-modifiable house structures, two splits were yielded. The primary split occurred for measured distance from home to nearest agricultural field, in which homes less than

2,204 feet (n=17) led to detection frequency of 59% in house dust while homes greater than or equal to 2,204 feet (n=4) led to a detection frequency of 0%. This split was not statistically significant (p=0.09). A second split occurred based on whether there was carpet in the home. For homes with carpet (n=10) detection frequency was 80% while in homes without carpet (n=7) detection frequency was 29%. This split was not statistically significant (p=0.18).

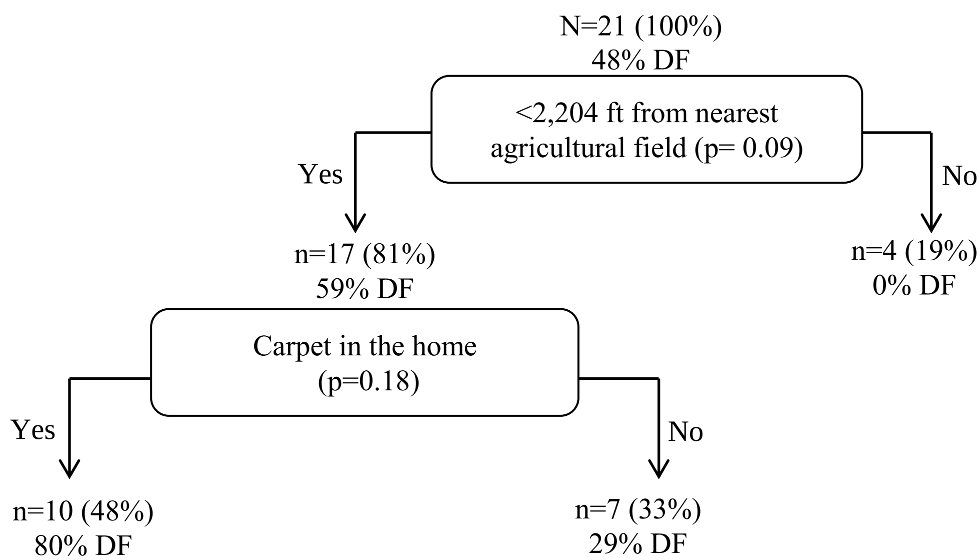


Figure 6-11: Classification Tree for Bifenthrin CART 6 Model - Non-Modifiable Housing Structure Factors Influencing Bifenthrin in House Dust

6.3.1.7 All Potentially Influential Factors on Detection Frequency in House Dust (CART 7A and CART 7B)

For the bifenthrin CART 7A model, which combined factors related to the air infiltration pathway and soil track-in pathway, household-level factors that are modifiable behaviors and non-modifiable house structures, and nearby with agricultural applications, the only split that occurred was once again based on 77 pounds of bifenthrin applied per square mile within the past year (p=0.06) as was the case for the air infiltration pathway factors in CART 3A and soil track-in pathway factors in CART 4A.

For the bifenthrin CART 7B model, which removed nearby agricultural applications from consideration, the first split occurred based on ≥ one farmworker per 1,000 ft^2 (p=0.09). For households that met this condition (n=13) detection frequency was 69%, while homes that did not meet this condition (n=8) detection frequency was 12%. The second split occurred at distance from home to nearest agricultural field, in which homes of less than 2,204 feet (n=11) led to detection frequency of 82% in house dust while homes at least this distance (n=2) led to a detection frequency of 0%. This split was not statistically significant (p=0.09). A final split occurred based on whether there was carpet in the home. For homes with carpet (n=8) detection frequency was 100% while in homes without carpet (n=3) detection frequency was 33%. This split was not statistically significant (p=0.18). A summary of all CART model outcomes for bifenthrin can be viewed in Table 6-6 and in Figure 6-14, the CART model outcomes can be seen in the form of a causal diagram.

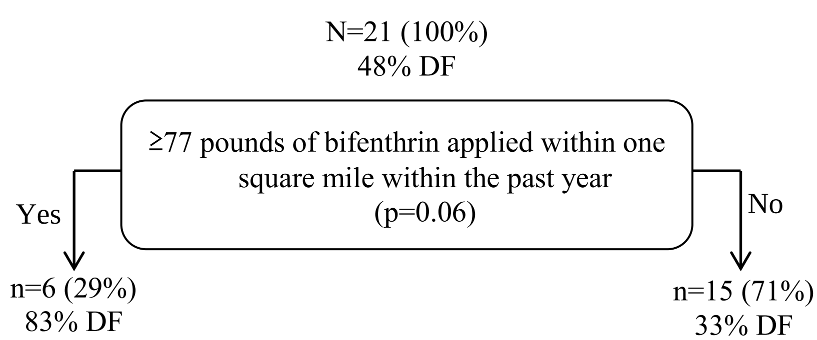


Figure 6-12: Results of Bifenthrin CART 7A Model: All Potentially Influential Factors on Detection Frequency in House Dust *with* Agricultural Applications Considered

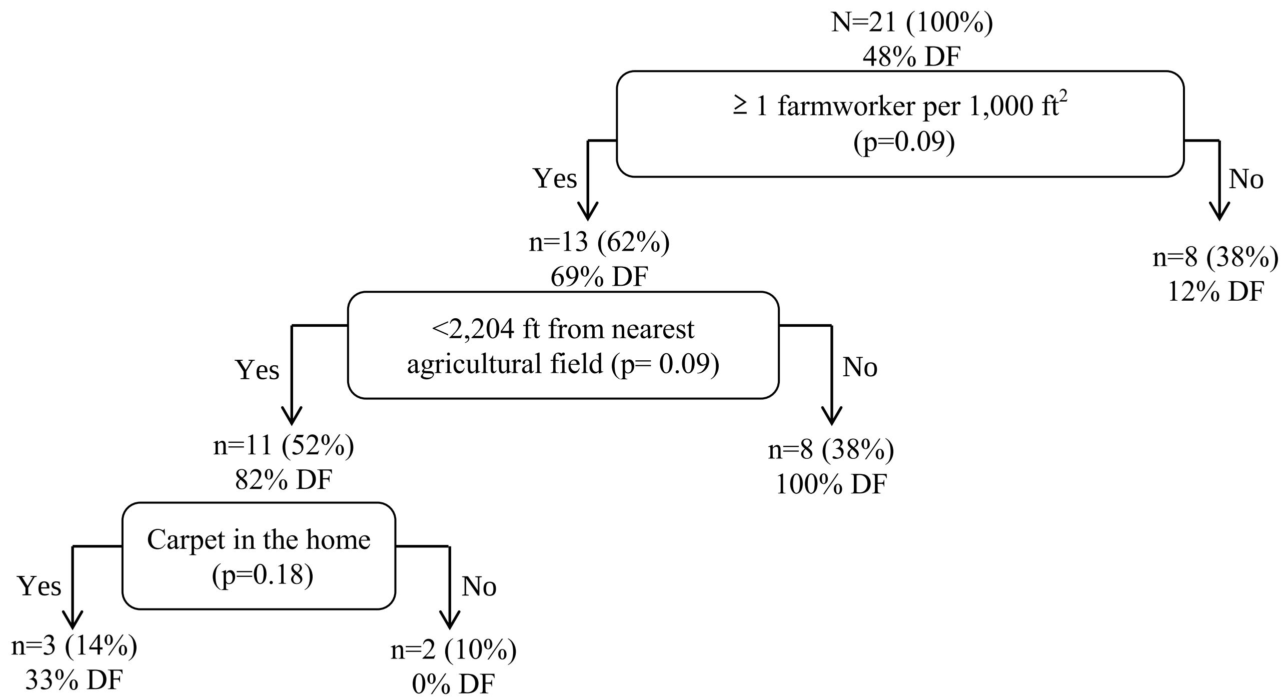


Figure 6-13: Results of Bifenthrin CART 7B Model: All Potentially Influential Factors on Detection Frequency in House Dust without Agricultural Applications Considered

Table: 6-6: Summary of Bifenthrin CART Models Outcomes

Media	**CART Split**	**Y/N***	**n (%)**	**DF**	**p-value**
Outdoor air- all factors combined	≥0.5 pound of bifenthrin applied within one square mile of home one month prior to sampling	Y	3(14)	100	0.12
		N	18 (86)	33	
Outdoor soil- all factors combined	<22,000 pounds of bifenthrin applied throughout Yuma County one year prior to sampling	Y	9 (43)	78	0.03
		N	12 (57)	8	
House dust - air infiltration factors -with agricultural applications	≥77 pounds of bifenthrin applied within one square mile within past year	Y	6 (29)	83	0.06
		N	15 (71)	33	
House dust - air infiltration factors -without agricultural applications	< 2,204 feet from nearest agricultural field	Y	17 (81)	59	0.09
		N	4 (19)	0	
	House ≥ 695 $feet^2$	Y	14 (67)	71	1.00
		N	3 (52)	0	
House dust via soil track-in factors -with agricultural applications	≥77 pounds of bifenthrin applied per square mile within past year	Y	6 (29)	83	0.06
		N	15 (71)	33	
House dust via soil track-in factors -without agricultural applications	≥1 farmworker per 1,000 $feet^2$	Y	13 (62)	69	0.09
		N	8 (38)	12	
	House <1,408 $feet^2$	Y	11 (52)	82	1.00
		N	2 (10)	0	
House dust - modifiable factors	Farmworkers remove shoes earlier (before arriving home or right away upon arriving home)	Y	16 (76)	67	0.01
		N	5 (24)	0	
House dust- non- modifiable factors	<2,204 feet from nearest agricultural field	Y	17 (81)	59	0.09
		N	4 (19)	0	
	Carpet in the home	Y	10 (48)	80	0.18
		N	7 (33)	29	
House dust- all factors combined -with agricultural applications	≥77 pounds of bifenthrin applied within one square mile within past year	Y	6 (29)	83	0.06
		N	15 (71)	33	
House dust- all factors combined -without agricultural applications	≥1 farmworker per 1,000 $feet^2$	Y	13 (62)	69	0.09
		N	8 (38)	12	
	<2,204 feet from nearest agricultural field	Y	11 (52)	82	0.09
		N	8 (38)	100	
	Carpet in the home	Y	3 (14)	33	0.18
		N	2 (10)	0	

*Y/N= Yes/No ~p-value for McNemar's test

Outdoor Air → **Air Infiltration** → **Indoor Air**

CART 1 - All Factors Influencing Outdoor Air

- ≥ 0.50 pound of bifenthrin applied within one square mile of home one month prior to sampling (p=0.12)

CART 2 - All Factors Influencing Outdoor Soil

- < 22,000 pounds of bifenthrin applied throughout Yuma County one year prior to sampling (p=0.002)

CART 3A/3B - Air Infiltration Pathway Factors

-With agricultural applications considered (3A):

- ≥ 77 pounds of bifenthrin applied within one square mile of home a year prior to sampling (p=0.06)

-Without agricultural applications considered (3B):

- <2,204 ft from nearest agricultural field (p=0.09)
- House ≥695 ft^2 (p=1.00)

CART 4A/4B - Soil Track-in Pathway Factors

-With agricultural applications considered (4A):

- ≥ 77 pounds of bifenthrin applied within one mile of home one year prior to sampling (p=0.06)

-Without agricultural applications considered (4B):

- ≥1 farmworker per 1,000 ft^2 of home (p=0.10)
- Home <1,408 ft^2 (p=1.00)

CART 5 - Modifiable Household Behaviors

- Farmworkers removing shoes earlier (p=0.04)
- Residential pesticides used (p=0.58)

CART 6 - Non-Modifiable House Structure Factors

- Nearest agricultural field <2,204 ft away (p=0.09)
- Carpet in the home (p=0.18)

CART 7A/7B - All Factors Influencing House Dust

-With agricultural applications considered (7A):

- ≥ 77 pounds of bifenthrin applied within one square mile of home a year prior to sampling (p=0.06)

-Without agricultural application considered (7B):

- ≥1 farmworker per 1,000 ft^2 of home (p=0.10)
- <2,204 ft from nearest agricultural field (p=0.09)
- Carpet in home (p=0.18)

Outdoor Soil → **Soil Track-in** → **Indoor House Dust**

Figure 6-14: Results of 7 CART Models Built to Identify Influential Factors on Bifenthrin Detection Frequency in Outdoor Soil and Air and Indoor House Dust

6.3.2 Permethrin CART Results

6.3.2.1 Potentially Influential Factors on Detection Frequency in Outdoor Air (CART 1)

For the permethrin CART 1 model (Figure 6-16), which assessed potential influential factors on detection frequency in outdoor air, the primary, and sole split was based on pounds of permethrin applied agriculturally throughout Yuma County one month prior to sampling. For homes where ≥11, 000 pounds of permethrin had been applied throughout Yuma County one month before it was sampled (n=3) detection frequency was 67%, while for homes that had less than 11,000 pounds (n=18) detection frequency was 6%. This was a statistically significant split (p=0.04).

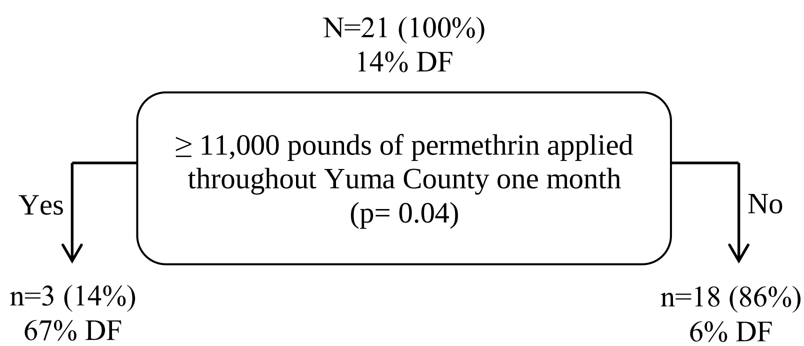


Figure 6-15: Classification Tree for Permethrin CART 1 Model - Factors Influencing Permethrin Detection Frequency in Outdoor Air

6.3.2.2 Potentially Influential Factors on Detection Frequency in Outdoor Soil (CART 2)

For the permethrin CART 2 model (Figure 6-16), which assessed potential influential factors on permethrin in outdoor soil the primary, and sole, split occurred based on number of farmworkers in the home. For homes with at least 3 farmworkers (n=2) detection frequency was 0%, while for homes with less than 3 farmworkers (n=19) detection frequency was 95%. This was a statistically significant split (p=0.01).

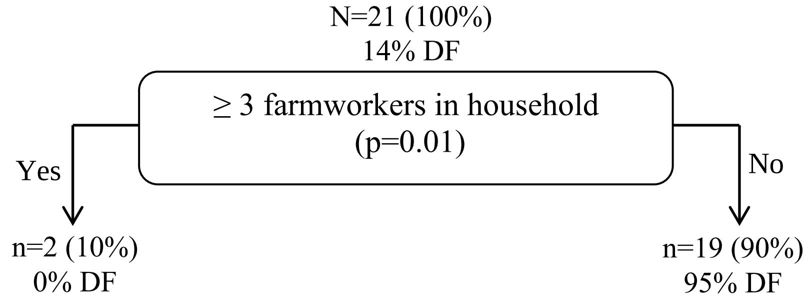


Figure 6-16: Classification Tree for Permethrin CART 2 Model - Factors Influencing Permethrin Detection Frequency in Outdoor Soil

6.3.2.3 Potentially Influential Air Infiltration Pathway Factors on Detection Frequency in House Dust (CART 3A and CART 3B)

For permethrin CART 3A and CART 3B models, which focused on air infiltration pathway factors when nearby agricultural applications of pesticides were considered (CART 3A) and not considered (CART 3B), no differences emerged, so a single depiction of the CART 3A/3B model can be seen in Figure 6-17. For homes that were cooled less than 7 months of the year (n=15) the detection frequency was 100%. For homes with at least 7 months of year of cooling (n=6) the detection frequency was 67% (p=0.05). This second split was based on months of heating per year. For homes that heated for less than 5 months of the year (n=4) detection frequency was 100%, while homes that heated for at least 5 months of the year (n=2) detection frequency was 0%. This split was not statistically significant (p=0.10).

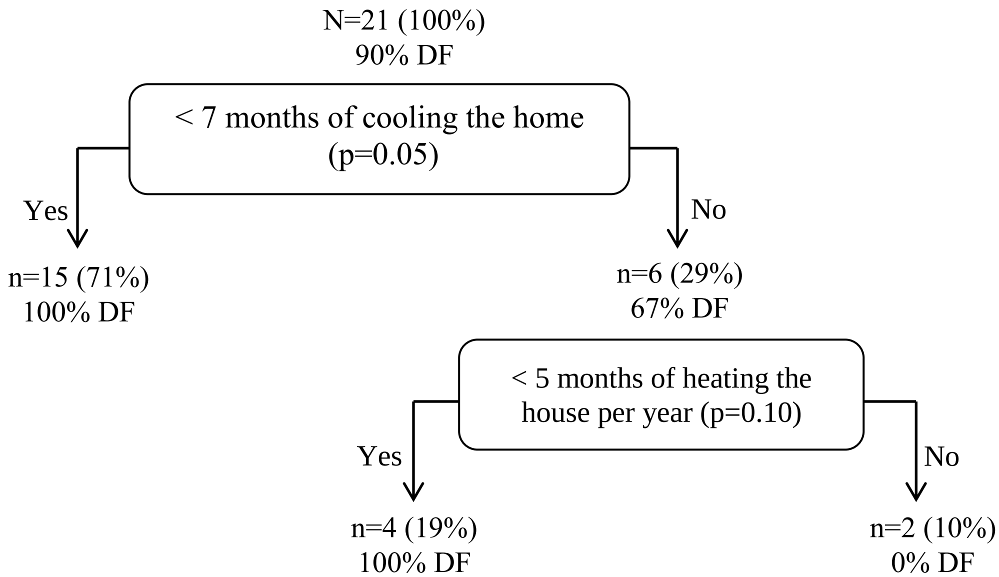


Figure 6-17: Classification Tree for Permethrin CART 3A/3B Model- Air Infiltration Factors Influencing Permethrin Detection Frequency in House Dust

6.3.2.4 Potentially Influential Soil Track-in Pathway Factors on Detection Frequency in House Dust (CART 4)

For the permethrin CART 4 model, which assessed factors influencing indoor house dust of permethrin due to soil track-in pathway factors, a classification tree could not be built based on lack of fulfillment of the "minimum split" requirement.

6.3.2.5 Modifiable Household Behaviors on Detection Frequency in House Dust (CART 5)

For the permethrin CART 5 model (Figure 6-18), which assessed modifiable household behaviors that could influence permethrin detection frequency in indoor house dust, two splits that emerged based on months of cooling and heating per year.

This classification tree matched that of factors related to the air infiltration pathway, described previously.

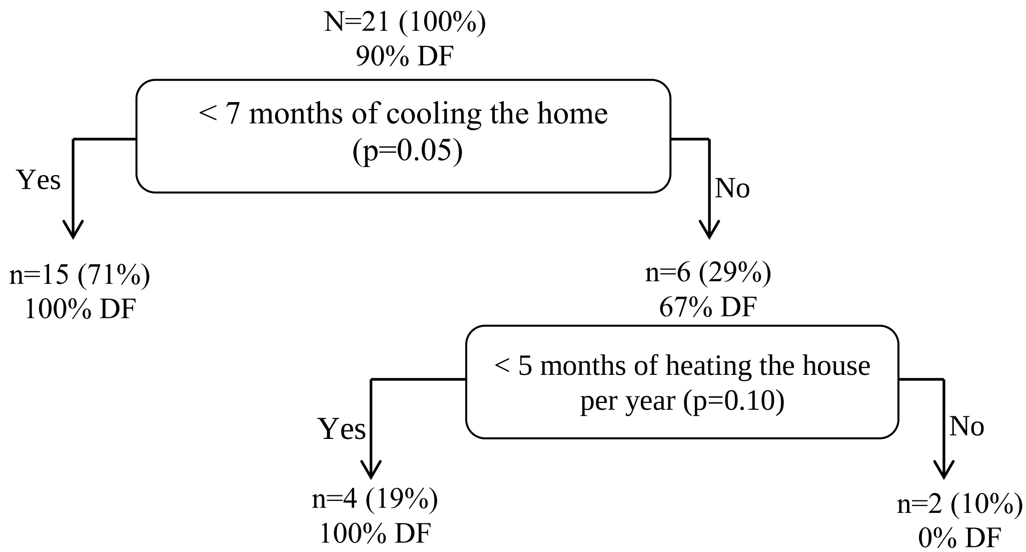


Figure 6-18: Classification Tree for Permethrin CART 5 Model – Modifiable Household Behaviors Influencing Permethrin Detection Frequency in House Dust

6.3.2.6 Non-Modifiable House Structures on Detection Frequency in House Dust (CART 6)

For the permethrin CART 6 model, which assessed factors influencing indoor house dust of permethrin with respect to housing structure factors, a classification tree could not be built based on lack of fulfillment of the "minimum split" requirement.

6.3.2.7 All Potentially Influential Factors on Detection Frequency in House Dust (CART 7A and CART 7B)

No differences could be seen for the permethrin CART 7A model, which combined factors related to the air infiltration pathway and soil track-in pathway, household-level factors that are modifiable behaviors and non-modifiable house structures, along with agricultural applications nearby, and the permethrin CART 7B model, which removed consideration of agricultural applications. Therefore, a single depiction of the permethrin CART 7A/7B model can be seen in Figure 6-19. For the permethrin CART 7A/7B model, two splits emerged based on months of cooling per year and heating per year. This classification tree matched the CART models built for factors related to air infiltration pathway and modifiable household behaviors, described previously. A summary of all CART results for permethrin can be viewed in Table 6-7 and in Figure 6-20, the CART model outcomes can be seen in the form of a causal diagram.

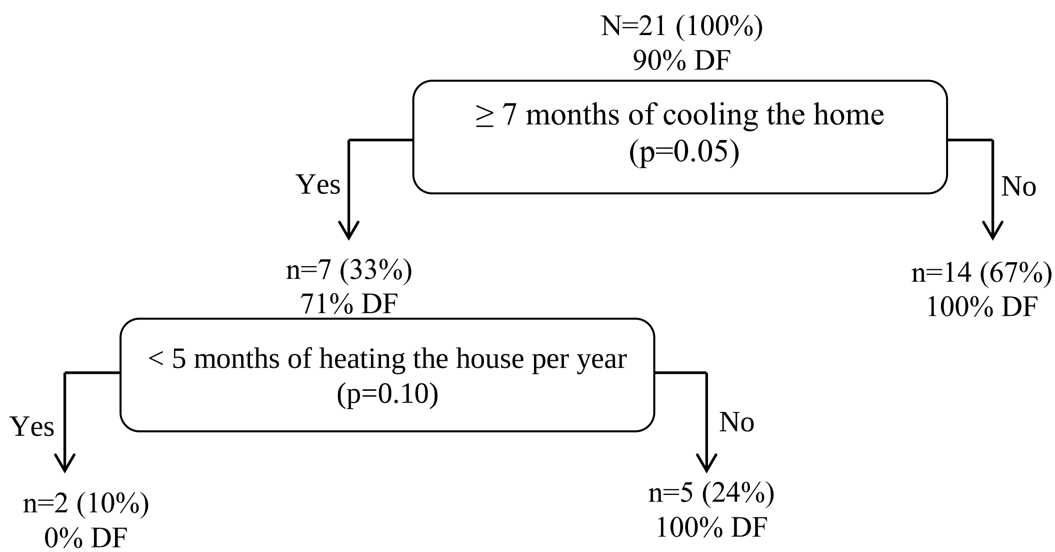


Figure 6-19: Results of Permethrin CART 7A/7B Models - All Potentially Influential Factors on Permethrin Detection Frequency in House Dust

Table: 6-7: Summary of Permethrin CART Models Outcomes

Media	**CART Split**	**Y/N***	**n (%)**	**DF**	**p-value~**
Outdoor air- all factors combined	≥11,000 pounds of permethrin applied throughout Yuma County one month	Y	3 (14)	67	0.04
		N	18 (86)	6	
Outdoor soil- all factors combined	≥3 farmworkers in household	Y	2 (10)	0	0.01
		N	19 (90)	95	
House dust - air infiltration factors -with/without agricultural applications	<7 months of cooling the home	Y	15 (71)	100	0.05
		N	6 (29)	67	
	<5 months of heating the house per year	Y	4 (19)	100	0.10
		N	2 (10)	0	
House dust - soil track-in factors -with/without agricultural applications	No splits observed				
House dust - modifiable factors	<7 months of cooling the home	Y	15 (71)	100	0.05
		N	6 (29)	67	
	<5 months of heating the house per year	Y	4 (19)	100	0.10
		N	2 (10)	0	
House dust- non-modifiable factors	No splits observed				
House dust- all factors combined -with/without agricultural applications	<7 months of cooling the home	Y	7 (33)	71	0.05
		N	14 (67)	100	
	<5 months of heating the house per year	Y	2 (10)	0	0.10
		N	5 (24)	100	

*Y/N= Yes/No ~p-value for McNemar's test

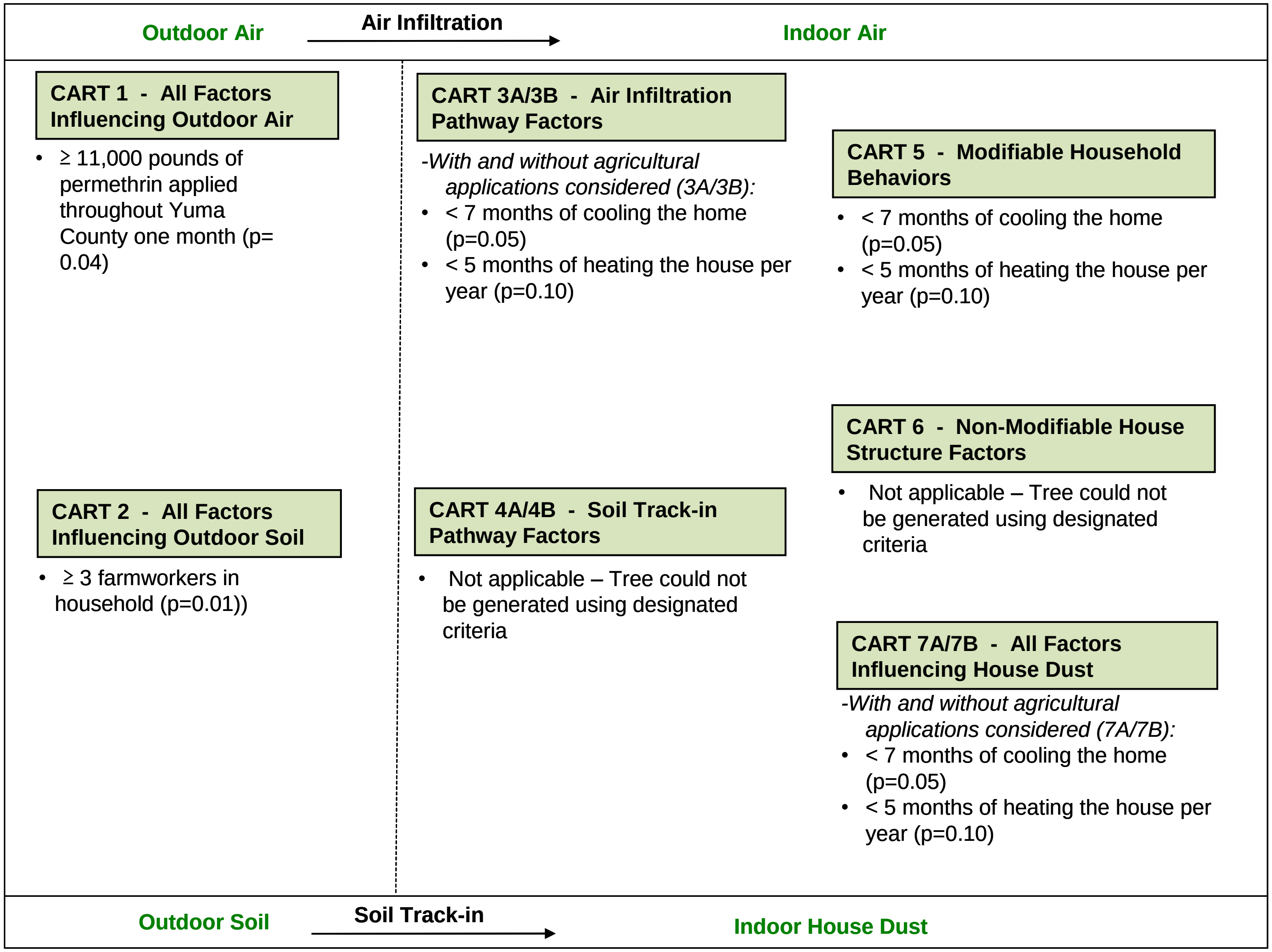


Figure 6-20: Results of 7 CART Model Built to Identify Influential Factors on Permethrin Detection Frequency in Outdoor Soil and Air and Indoor House Dust

6.3.3 Assessment of CART Model Effectiveness

6.3.3.1 Bifenthrin CART Models

All bifenthrin CART models were effective from the perspective of meeting the minimum split requirement and thus, it was considered "possible" to grow each tree. Next, all bifenthrin CART models were also effective from the perspective of being able to use the optimal CP value and as such, each tree was considered "uncompromised." However, from the perspective of assessing prediction accuracy, the bifenthrin CART models were not quite as effective. The misclassification rate/ prediction accuracy for the outdoor air was 43%/57%, outdoor soil was 33%/67%, and house dust was 43-52%/47-57%. Therefore, the bifenthrin CART models for outdoor air and outdoor soil were considered "moderately predictive" and for house dust ranged from "unpredictive" to "moderately predictive." A summary of these results can be seen in Table 6-6.

Table 6-8: Assessment of Effectiveness of CART Models Built for Bifenthrin

	Perspective I	**Perspective II**	**Perspective III**			
Bifenthrin CART	*Minimum split requirement met?*	*Optimal CP value used?*	*RNE*	*Xerror for CP used*	*MCR (%)*	*PA (%)*
1	Yes	Yes	0.43	1.00	43.00	57.00
2	Yes	Yes	0.38	0.88	33.25	66.75
3A	Yes	Yes	0.48	1.00	48.00	52.00
3B	Yes	Yes	0.48	1.00	48.00	52.00
4A	Yes	Yes	0.48	1.10	52.80	47.20
4B	Yes	Yes	0.48	0.90	43.20	56.80
5	Yes	Yes	0.48	0.90	43.20	56.80
6	Yes	Yes	0.48	1.00	48.00	52.00
7A	Yes	Yes	0.48	1.20	48.00	52.00
7B	Yes	Yes	0.48	1.00	48.00	52.00
Model Effective?	"possible" for 1-7B	"uncompromised" for 1-7B	"moderately predictive" for 1,2, 3A, 3B, 4B, 5, 6, 7A, & 7B "unpredictive" for 4A			

6.3.3.2 Permethrin CART Models

For permethrin, the soil track-in CART models (4A/4B), along with the non-modifiable factors CART model (6) did not meet the minimum split requirement making it "impossible" to grow these tree, and thus these CART models were not effective from this perspective. For the remaining CART models that did meet the minimum split requirement (CART models 1,2,3A, 3B, 5,7A, & 7B), several of the models were considered "compromised" because they were not able to use the optimal CP values (CART models 3A, 3B, 7A, & 7B) and thus were considered ineffective from this perspective. The outdoor air factors (CART 1) and outdoor soil factors (CART 2) were able to use the optimal CP values, designating them as "uncompromised." The misclassification rate/ prediction accuracy for the outdoor air was 14%/86%, outdoor soil was 5%/95%, and indoor house dust was 10-20%/ 80%-

90%. Therefore, the permethrin CART models for outdoor air and outdoor soil were considered "highly predictive" and for house dust were considered "highly predictive." A summary of these results can be seen in Table 6-7.

Table 6-9: Assessment of Effectiveness of CART Models Built for Permethrin

	Perspective I	**Perspective II**	**Perspective III**			
Permethrin CART	*Minimum split requirement met?*	*Optimal CP value used?*	*RNE*	*Xerror for CP used*	*MCR (%)*	*PA (%)*
1	Yes	Yes	0.14	1.00	14	86
2	Yes	Yes	0.14	0.33	5	95
3A	Yes	No	0.10	2.00	20	80
3B	Yes	No	0.10	1.50	15	85
4A	No	N/A	N/A	N/A	N/A	N/A
4B	No	N/A	N/A	N/A	N/A	N/A
5	Yes	No	0.10	2.00	20	80
6	No	N/A	N/A	N/A	N/A	N/A
7A	Yes	No	0.10	1.00	10	90
7B	Yes	No	0.10	1.00	10	90
Model Effective?	"impossible" for 4A, 4B, & 6 "possible" for 1,2,3A,3B, 5, 7A, & 7B	not applicable for 4A,4B, & 6 "compromised" for 3A, 3B,5,7A, &7B "uncompromised" for 1&2	not applicable for 4A,4B, & 6 "highly predictive" for 1,2, 3A, 3B, 5, 7A, &7B			

6.4 Discussion

6.4.1 Influence of Agricultural Pesticide Applications on Bifenthrin and Permethrin Detection Frequency in Outdoor Soil and Air

For both bifenthrin and permethrin, the influence of agricultural applications was more apparent for the outdoor air CART models compared to the outdoor soil CART models. The fact that the sole split for higher bifenthrin detection frequency in the outdoor air CART model was predicted by increased bifenthrin applications (p=0.12) suggests that bifenthrin is likely to be transported away from agricultural fields primarily through air transport. Likewise for permethrin, the sole split for increased detection frequency in the outdoor air CART model predicted by increased agricultural applications of permethrin (p=0.04), once again suggesting air transport of permethrin away from fields. It is notable that agricultural pesticide applications themselves are more influential than any household-level risk factors, including distance to an agricultural field, which often considered a proxy of agricultural pesticide transport through the air (Simcox et al., 1995; Richards et al., 2001; Quandt et al., 2004; Weppner et al., 2006; Coronado et al., 2011; Gunier et al., 2011). Yet, it is difficult to examine the implications of distance to nearest agricultural field when it is not possible to determine whether the pesticide of interest was actually applied in the nearest field or whether the home was down-wind from that specific field (Loewenherz et al., 1997; Curl et al., 2002; McCauley et al., 2003). The approach in the current study, which incorporates known applications of the agricultural pesticide of interest in a circular buffer around the house, as well as throughout the entire County, bypasses the limitations of the assessments related to distance between home and field. The finding that agricultural pesticide applications are better predictors than the home's distance to an agricultural field could offer an explanation for why many previous studies did not find an association between agricultural pesticides in the home and distance to the nearest agricultural field (Lu et al., 2000; Fenske et al., 2002; Curwin et al., 2005; Ward et al., 2006; Golla et al., 2012; Lozier et al., 2012).

On the other hand, for outdoor soil, the sole split for higher bifenthrin detection frequency was actually predicted by decreased agricultural pesticide applications ($p=0.03$). Although this was a rather unexpected finding, it may reflect differences in application by season. Of the four sampling trips (two in April 2011, one in October 2011, and one in February 2012), only the trip towards the end of February 2012 had <22,200 pounds applied throughout the County within a year prior, while this was not the case for homes sampled in April 2011 or October 2011. For the years 2006-2011, the peak application of bifenthrin in Yuma County generally occurred September- November (6,200 pounds-9,700 pounds) compared to December-August (990 pounds-4,400 pounds), and these autumn and winter months correspond to the time period in which bifenthrin is generally applied to lettuce in agricultural fields (Sugeng, 2011; AZDA, 2014). With the soil half-life of bifenthrin estimated to be up to 125 days (approximately 4 months) (WHO, 2011), it is possible that although actual less pounds of bifenthrin were applied a year prior to the February 2012 sampling trip, peak applications of that particular pesticide during the September-November time period may been at the peak accumulation in the outdoor soil, causing detection frequency in the soil to be associated with the February 2012 sampling trip.

In the outdoor soil CART model for permethrin, higher detection frequency was predicted by having less than three farmworkers in the household (p=0.01), which may actually indicate that soil take-home/soil track-in via farmworkers is not as significant of a pathway, indirectly lending credence to the relevance of the air transport pathway. This is supported by the findings in Chapter 5 of this dissertation where a weak negative correlation between number of farmworkers in the home and permethrin concentrations in the house dust is reported, suggesting that track-in of permethrin via farmworkers is unlikely to be the major transport pathway of this particular pesticide into the home. An alternative source of permethrin in outdoor soil could be from residential pesticide use, although this factor did not emerge as an influential split for detection frequency of permethrin in outdoor soil, indicating that any engagement in this household practice was of lesser influence. In Chapter 5 of this dissertation, it was cautioned that while an association between residential pesticide use and household levels of the measured pesticides was not observed, there could still be a contribution that is not captured statistically. In peer-reviewed literature, the reported effect of residential pesticide use on measured pesticide levels in the home have been mixed, although it should be remembered that all prior studies focused on house dust, while the current finding is related to outdoor soil. Interestingly, for the studies that were not limited to farmworker families, associations between residential pesticide use and pesticide levels in the house dust were observed (Freeman et al., 2004; Gunier et al., 2011; Deziel et al., 2013). On the other hand, for the studies that focused specifically on farmworker families, no association was observed between residential pesticide use and pesticide levels measured in the house dust (McCauley et al., 2001; Lu et al., 2000; McCauley et al., 2003; Curwin et al., 2005; Golla et al., 2012; Lozier et al., 2012). One possible reason for the discrepancy between non-farmworker and farmworker families could be reporting differences based on variations in perceptions between the two populations. For example, it is possible that those who work in agriculture do not consider the household products to be pesticides, since that is what they associate to be a workplace chemical. In the current study, an attempt was made to avoid this issue by asking participants if they use products “to control insects or plant growth in the house or garden”, rather than simply asking if they use pesticides. In addition, since a pesticide’s outdoor soil half-life may be shorter than the indoor house dust half-life (Paustenbach et al., 1997, Hwang et al., 2008), there could be differences between the two populations based on whether they predominantly applied pesticides indoors or outdoors.

Another possible explanation for the finding that having less than three farmworkers in the household was a predictor of soil detection frequency for permethrin is that detection frequency in soil is not so much a function of how many farmworkers in the household, but rather what type of agricultural pesticide each farmworker is exposed to in the fields. Using this logic, a family with two farmworkers in the household working in a field where permethrin is applied may result in a higher detection frequency of permethrin in outdoor soil than a family with four farmworkers in the household, but only one farmworker is exposed to permethrin at work. The general concept that pesticide detection at the home matches the type of pesticide used in the field is supported by Coronado et al. (2006), in which the type of agricultural pesticides detected in the urine of farmworker's children matched that of the pesticide used in the field where their parent(s) worked. It is a possible that this concept could be extended to support the notion that the more farmworkers of a given household that work with a certain type of pesticide in the field, the greater detection frequency of that specific pesticide would be in the home. To the knowledge of the author of this study, this has not been previously reported in the peer-reviewed literature, but it could be explored in future studies.

6.4.2 Influence of Agricultural Pesticide Applications on Bifenthrin and Permethrin Detection Frequency in House Dust

When agricultural applications were included as possible predictors for the CART models with an outcome of bifenthrin detection frequency in the house dust, increased bifenthrin applications within one square mile of the home within the year prior to sampling was consistently the only the only identified predictor ($p=0.06$). This is potentially concerning because it could imply that a certain "threshold level" of bifenthrin application in the nearby fields (77 pounds in this case) may make household-level factors become less influential. Thus, household-level factors that could potentially help prevent pesticide transport into the home may be less effective after the "threshold level" of bifenthrin application has been reached. This raises the question of whether families in agricultural communities that engage in household-level protective behaviors that they believe help prevent agricultural pesticides from entering their home (e.g., taking shoes off right away upon arriving home) have a false sense of security. For example, the author provided a thorough discussion in

Chapter 5 around the fact that farmworker-specific behaviors (i.e., removing shoes, changing out of work clothes, showering) were not associated with lower levels of agricultural pesticides in the house dust, although many of the farmworkers reported engaging in these behaviors. It is notable that the small sample size of the current study makes it difficult to say with certainty whether bifenthrin applications would remain the primary predictor of bifenthrin detection frequency if the sample size was increased. This finding adds evidence to the idea that living in an agricultural community increases agricultural pesticide detection frequency in house dust, regardless of whether the family works directly in the agricultural fields. However, based on previous studies in the peer-reviewed literature, the levels would still likely be higher in farmworker homes compared to non-farmworker homes. Curwin et al., (2005) reported that when house dust was sampled in farmworker homes and non-farmworker homes in an agricultural community, the researchers found that agricultural pesticides were detected in both types of homes, but that levels were higher in the farmworkers' homes. Similarly, in Lu et al., (2000), pesticides in house dust was highest in homes of pesticide applicators, followed by homes of farmworkers, and lower in homes of non-farmworkers. In the current study, only homes with farmworkers were included for sampling. In the future, homes that have no farmworkers, but the residents' but are living in the same agricultural community could additionally be sampled to determine if agricultural pesticides can be detected in these households and compared to the agricultural pesticide levels to those of the farmworker households.

The influence of agricultural applications was not a compelling predictor for permethrin detection frequency in house dust in any of the CART models (CART 3A, CART 4A, and CART 7A). This does not necessarily mean that agricultural applications of permethrin do not pose a threat to nearby communities, but rather it suggests that factors at the household level may be effective at reducing air infiltration and soil track-in into the home. It may also mean that in this particular dataset, permethrin applications did not reach the required "threshold level" that would cause household-level factors to become less effective, as was previously suggested for bifenthrin. Another reason why the agricultural applications of permethrin may not appear to be as influential as the agricultural applications of bifenthrin may be due to the much shorter soil half-life of permethrin compared to that of bifenthrin. Finally, this could be caused by fact that residential applications of permethrin may also contribute to the house dust. Please refer to Section 6.4.1 for a discussion on residential pesticide use and its effect on

6.4.3 Household-Level Factors as Predictors of Bifenthrin Detection Frequency in House Dust

It is concerning to realize that the effectiveness of making changes at the household level may be limited in an agricultural community, depending on the agricultural pesticide of interest and how much of that pesticide is applied nearby. Nonetheless, exploration of household-level factors is still a worthwhile endeavor. Removing agricultural applications as predictors from the CART models provided an opportunity to identify household level predictors that could not be seen when agricultural applications were considered. For bifenthrin, increased detection frequency in house dust was predicted by homes less than 2,204 feet (0.42 mile) from the nearest agricultural field ($p=0.09$). This finding supports the idea that pesticides applied in agricultural fields can enter into nearby homes via air infiltration and that distance to the field is among the most influential factors on detection frequency house dust. Also, the finding was very similar to that of the results in Chapter 5 of this dissertation, where a significant association was seen between bifenthrin in house dust and a distance of less than 0.5 mile between the home and nearest field. Please also refer to Chapter 5 for a complete discussion on the relationship between distance between home and nearest agricultural field in the current study, as well as in other studies found in the peer-reviewed literature. The non-modifiable nature of this predictor is concerning for families living near agricultural fields because even if families engage in behaviors to help prevent transport into their homes, the effect of these efforts may be limited.

Another predictor that emerged was that of square footage of the home for both the air infiltration and soil track-in CART models, although the findings were a bit different for each pathway. Among air infiltration factors, the house being at least 695 ft^2 was predictive of higher bifenthrin detection frequency in the house dust. Among soil track-in factors, the house being less than 1,408 $feet^2$ was predictive of higher bifenthrin detection frequency in house dust. This finding does add supplemental information to that of Chapter 5 of this dissertation, where a positive correlation between square footage of the home and bifenthrin levels in house dust was found. There, it was posited that for agricultural pesticides that enter the house through air infiltration, it would be expected to observe an increased level in the dust for homes with larger square footage since a larger house has a greater area of entry points for which pesticides can infiltrate. This idea is supported by McCauley et al., (2013), which also found a correlation between house square footage and agricultural pesticide levels in the house dust. It was further posited that for agricultural pesticides that enter the home through soil track-in, a larger square footage may cause a decreased level of that pesticide because of the potential to track the pesticide throughout a larger surface area, diluting the pesticide. This idea is based on the finding of Hunt et al., (2006), which reported that picking up previously deposited dust or soil in the home contributes more to the wide-spread contamination of the floor surface compared to the initial track-in of soil. The findings from the CART models reflect this idea that square footage of the home may be important, yet the type of effect observed may depend on the pathway in which the agricultural pesticide enters the home. It is also notable that square footage is not a modifiable factor.

Another non-modifiable predictor for increased detection frequency of bifenthrin in house dust was having at least one farmworker per 1,000 feet^2 of the home ($p=0.10$). It is possible that some of the contribution to the house dust could be from farmworkers bringing bifenthrin home with them on their shoes, clothes, and skin, but it should be noted that none of splits that emerged pointed towards any particular behaviors of the farmworkers. The finding at hand is contrary to that of McCauley et al., (2001) and McCauley et al., (2003) where no associations were found between levels of agricultural pesticides in the house dust and farmworkers and agricultural owners/managers per square footage, respectively. This is also contrary to the finding in Chapter 5 where the correlation between farmworkers and bifenthrin in house dust weakened when adjusting the number of farmworkers by square footage of the home. Nonetheless, the current finding is more intuitive than what was found in Chapter 5, despite the lack of similar reports in the literature to support this claim. It is possible that the ability of CART to take into consideration multiple factors and the interactions among these factors, allowed relevant predictors to surface, such as having at least one farmworker per 1,000 feet^2 of the home, that would not been seen through the univariate approach. It is important to remember that all homes in the current study did include at least one farmworker, and therefore, it is not possible to compare the difference between the levels in farmworker and non-farmworker house dust. Finally, it is notable that this finding is not a feasibly modifiable factor at the household level, once again highlighting the general concern of simply living in an agricultural community.

Next, having carpet in the house emerged as a predictor of increased detection frequency of bifenthrin in the house dust (p=0.18). This split is consistent with the finding in Chapter 5 of this dissertation where there was a positive correlation between having carpet and concentration of bifenthrin in the house dust. This split is also in congruence with prior research that found that removal of semi-volatile organic compounds from carpet fibers and the underlying foam pad is generally ineffective through mechanical cleaning processes (Hunt et al., 2008; Shin et al., 2013), suggesting that pesticides may accumulate more easily in homes with carpet. This may also support the finding in Quandt et al., (2004) in which homes categorized as “difficult to clean” had an increased odds of detecting both residential and agricultural pesticides in homes. Chapter 5 of this dissertation offers additional information related to the potential role of carpet on levels in the house dust, both from the current study and from prior studies in the peer-reviewed literature. Like the other previously mentioned factors, having carpet is not feasibly modifiable, particularly in low-income communities that do not necessarily have the finances and resources to replace flooring.

The sole predictor for modifiable behaviors on increased bifenthrin detection frequency in house dust was based on farmworkers actually removing shoes earlier upon arriving home ($p=0.04$). In Chapter 5 of this dissertation, a very thorough discussion related to the implications of shoe removal can be seen. There, it was suggested that earlier shoe removal may not be actually be as effective at reducing pesticide levels in the house as is widely assumed, and this suggestion is supported by numerous peer-reviewed studies.

Therefore, the household-level factors as predictors of bifenthrin detection frequency in house dust are overwhelmingly non-modifiable (i.e., distance, square footage, number of farmworkers per square footage, having carpet), with the only potentially modifiable predictor, time until shoe removal, being counter-intuitive and potentially ineffective. Results of this study suggest that families may be limited in their ability to protect themselves from agricultural pesticides being transported into their homes, suggesting that major policy initiatives placing the burden on the agricultural growers and chemical producers may be necessary to truly prevent agricultural pesticides from being transported away from fields and into homes.

6.4.4 Household-Level Risk Factors as Predictors of Permethrin Detection Frequency in House Dust

While influential factors predictive of permethrin detection frequency in house dust were much more limited, they are optimistically modifiable. The only influential splits that occurred, both when agricultural applications were considered and when they were not considered, were cooling the home less than 7 months of the year (p=0.05) and heating the home less than 5 months of the year (p=0.10). The fact that these factors were influential splits for 3 different CART models (CART 3, which focused on air infiltration factors, CART 5, which focused on modifiable household behaviors, and CART 7, which combined all potentially influential factors) makes a compelling argument that these factors are important predictors. These findings were sensible because the use of a heating or cooling system generally decreases ventilation into the house compared to opening up windows and doors, a factor that was considered separately from heating and cooling the home. Results of multiple previous studies found that air conditioning in the home was associated with lower levels of contaminants both for particulate matter (Suh et al., 1992; Suh e al., 1994; Wallace 1996; Allen et al., 2012) and volatile organic compounds (Clobes et al., 1992; Dales et al., 2008), and each of these studies attributed their findings to a lower air exchange rate due to the house being more tightly sealed. Additionally, Harnly et al., (2009) reported decreased agricultural pesticide levels in house dust in homes with an air conditioner. Interestingly, in Chapter 5 of this dissertation, frequency of cooling and heating the home were not well associated with concentration of bifenthrin in the house dust. This, once again, sheds light on the advantage of CART as a multi-variate analysis that is able to assess multiple factors at once and identify the best predictors among the many potentially influential factors.

Since cooling and heating the home can be attributed to the air infiltration pathway rather than the soil track-in pathway, it is suspected that the influence of permethrin is also primarily related to living near an agricultural field. This finding provides more evidence that simply living in an agricultural community may impacts agricultural pesticide levels in the home, regardless of whether or not the family directly works in the agricultural industry. However, as mentioned previously, future studies could evaluate this hypothesis through a case-control study, comparing agricultural pesticide levels in farmworker and non-farmworker homes within the same agricultural community. Future research should also focus on assessing cooling and heating patterns in the home more closely in order to better understand how to maximize air exfiltration, yet minimize air infiltration. It is, of course, necessary to remember that cooling and heating can be costly practices, and thus, it may not be practical to advise families to increase the cooling and heating of their home. Instead, it would be wise to find creative methods to decrease the air exchange rate without compromising temperature control of the home, such as exploring the influence of different types of air filters.

It is important to remember that CART is largely focused on developing a predictive model that can be used with new datasets; therefore, although there may be more influential factors, they may not be identified as predictors in the model because they would not be effective a maximizing predictive ability. This also highlights a difference between CART models from linear/logistic regression models. For linear/logistic regression models, the user would be able to choose predictors of interest and quantify how well they work in the model; on the other hand, CART simply removes less important predictors limiting the user's ability to quantify their influence at all. It would be wise to consider factors that increased levels in the house dust from Chapter 5 of this dissertation through univariate analyses, such as not having outdoor mats and cleaning the house less frequently, in combination with to the factors identified through the CART models for future studies.

6.4.5 Effectiveness of the CART Models

Effectiveness of the CART models for predicting bifenthrin and permethrin detection frequency in this study varied. From the perspective of meeting the minimum split requirement and being able to use the optimal CP value, which are necessary to actually build a tree and minimize the *xerror*, all of the CART models for bifenthrin detection frequency in outdoor air, outdoor soil, and indoor house dust were quite effective. Yet, when the prediction accuracy of each model was calculated, they were lower than expected. For bifenthrin it can be seen that the soil track-in model that considered nearby agricultural applications only had a prediction accuracy of 47%, rendering it completely "unpredictive" as this is even below the commonly accepted random probability of 50%. The remaining CART models built for bifenthrin detection frequency in house dust fared a bit better, with prediction accuracy above 50%. Although prediction accuracy can only be deemed "moderately predictive" for these models, it is still reasonable to give credibility to the factors identified. Models with this level of prediction accuracy may be a valid first step in the screening process of identifying more influential factors on agricultural pesticide transport into homes from among the otherwise overwhelmingly higher number of potential factors. Identified factors can be further explored in subsequent studies that are designed to more closely assess the influence of particular factors, especially if they are modifiable factors at the household level through behavioral changes. It may be equally informative to identify factors that are not modifiable, yet influential, in highlighting the limitation of household level changes and promoting other approaches to reduce agricultural pesticides in house dust, such as more controlled applications at the agricultural field. In fact, CART models have been previously used for screening purposes in other contexts (Reichard et al., 1997; Fu et al., 2004; Deconinck et al., 2005) lending support for the use of the CART models from the current study for screening initiatives as well.

The effectiveness of the CART models built for permethrin detection frequency was quite different than those for bifenthrin. It was not even possible to grow a tree for soil track-in factors (with and without agricultural applications considered) or for non-modifiable factors due to the inability to meet the minimum split requirement. In addition, among the trees that could be built, it was not possible to prune some of these trees with the optimal CV value. Nonetheless, the final pruned trees were overwhelmingly considered to be “highly predictive.” It is notable that very few factors were identified through the CART models for permethrin detection frequency.

For both bifenthrin and permethrin, the prediction accuracy was higher in the outdoor air and outdoor soil, compared to the indoor house dust. Given this, along with the fact that identified splits for air and soil focused heavily on pesticide applications, suggests that pesticide detection frequency in outdoor media at farmworkers' homes is well-predicted by nearby agricultural applications. This could suggest that it is easier to predict pesticide transport away from agricultural fields into the general community nearby, yet truly understanding the intricacies of how agricultural pesticides enter into homes is the more difficult task at hand This complexity underscores the reasoning behind building multiple different CART models in attempt to understand all the factors that affect pathways of pesticides into the house dust and whether these factors are modifiable or non-modifiable at the household level. It is also possible that the complexity related to detection frequency in outdoor soil and air were simply not captured in the CART models in this study because rather than being driven by factors at the household level, they could be more heavily driven by other types of factors, such as a weather conditions or chemical characteristics. In future studies, CART models that incorporate additional factors external to the household be informative.

An interesting trade-off appeared when comparing the overall effectiveness for the bifenthrin and permethrin CART models. For bifenthrin, more factors were identified, yet prediction accuracy was lower. On the other hand, for permethrin, fewer factors were identified, but these factors were ultimately better predictors. There is an advantage to both of these results. For screening purposes, there is emphasis on identifying a range of factors rather than on the prediction accuracy because the intention is to further examine each factor in more targeted studies. On the other hand, models with high prediction accuracy may be necessary before designing large-scale interventions aimed at making changes at the household or community level.

6.4.6 Conclusions

The current Chapter successfully identifies relevant household-level risk factors for increased in-home agricultural pesticide levels, fulfilling the third specific aim of this dissertation. The influence of agricultural pesticide applications was more apparent for the outdoor air CART models compared to outdoor soil CART models for both bifenthrin and permethrin, suggesting that the primary transport away from agricultural fields into the general community is through the air. Results of the CART models suggest that living near an agricultural field, regardless of whether the family works directly in agriculture, may influence pesticide levels in the house dust, particularly for bifenthrin. It is possible that a certain "threshold level" of agricultural pesticide application in the nearby area may reduce the influence of household-level factors.

The hypothesis associated with the third major aim, which was that that most of the household-level risk factors associated with in-home agricultural pesticide levels are structural characteristics related to the air infiltration pathway, and that these factors will not be easily modifiable at the household-level was partially confirmed and partially rejected. For bifenthrin, important household-level risk factors were identified for both the infiltration and soil track-in pathways. Most identified household-level predictors of bifenthrin detection frequency in house dust found to not be easily modifiable by the family, including closer distance between home and field, having carpet in the house, square footage of the home, and having at least one farmworker per 1,000 ft^2 in the household. For permethrin, the only factors identified as predictors of detection frequency in house dust were less frequent cooling and heating of the home, which are relevant to the air infiltration pathway. However, the fact that a CART model for soil track-in factors could not be built prevented exploration of contributions via the soil track-in pathway. Frequency of cooling and heating the home may be modifiable factors in the household, and therefore, it is recommended that these factors be examined more closely in future studies.

Prediction accuracy of the CART models varied, but overall prediction accuracy was higher for permethrin compared to bifenthrin. There was an apparent trade-off between number of predictors and prediction accuracy; increased number of predictors may be useful for screening purposes, while increased prediction accuracy may be necessary for implementing large-scale interventions in homes and communities.

CHAPTER 7

USING THE HEALTH RISK ASSESSMENT PROCESS TO ASSESS HEALTH RISKS OF RESIDENTIAL EXPOSURE TO AGRICULTURAL PESTICIDES

7.1 Introduction

7.1.1 Defining Risk

In the field of environmental health, risk is defined as the "systematic scientific characterization of potential adverse health effects resulting from human exposures to hazardous agents or situations" (Faustman and Omenn, 2001; Omenn and Faustman, 2002). In its most simplistic form, risk is a function of hazard and exposure. A hazard is a source of potential harm, adverse health effects, or damage, such as cancer or endocrine disruption. Exposure is the contact between the hazard of interest and the individual. The level of exposure depends on the length and frequency of the activity, concentration of the chemical, how the chemical is used, and whether any precautionary measures taken, such as use of personal protective equipment (Robson and Ellerbusch, 2007).

7.1.2 Acceptable Risk and Human Health Risk Assessment

If a given situation were to present no hazard or have no exposure potential, then the level of risk would be zero. Yet, it is understood that no situation truly comes with "zero risk" (Robson and Ellerbusch, 2007). In one of the most influential books that discusses the nexus between risk and safety in society, *Of Acceptable Risk: Science and the Determination of Safety,* the author stated,

> “"Nothing can be absolutely free of risk. One can't think of anything that isn't, under some circumstances, able to cause harm. Because nothing can be absolutely free of risk, nothing can be said to be absolutely safe. There are degrees of risk, and consequently there are degrees of safety." (Lowrance, 1976)

Since there can never be “zero risk,” the endeavors of environmental health and public health practitioner should involve the determination of an “acceptable risk” and then focus should be on risk reduction techniques to reach an “acceptable risk level.” However, the notion of “acceptable risk” is controversial because individuals or groups may vary in their opinion of what level of risk is acceptable, since this is rooted in individual perceptions, reactions, and emotions, along with economic or political agendas. Nonetheless, it is crucial to determine an “acceptable risk level” to set guidelines and standards for the purposes of regulation or recommendations.

The process of assessing exposure to a health hazard in the environment and determining whether that exposure is within an “acceptable risk level” for given health effects is known as a human health risk assessment. The human health risk assessment process involves four major steps as shown in Figure 7-1: (1) hazard identification, (2) dose-response assessment, (3) exposure assessment, and (4) risk characterization. The current study used a human health risk assessment approach, described below, in order to assess the risk of chronic health effects due to residential exposure to agricultural pesticides.

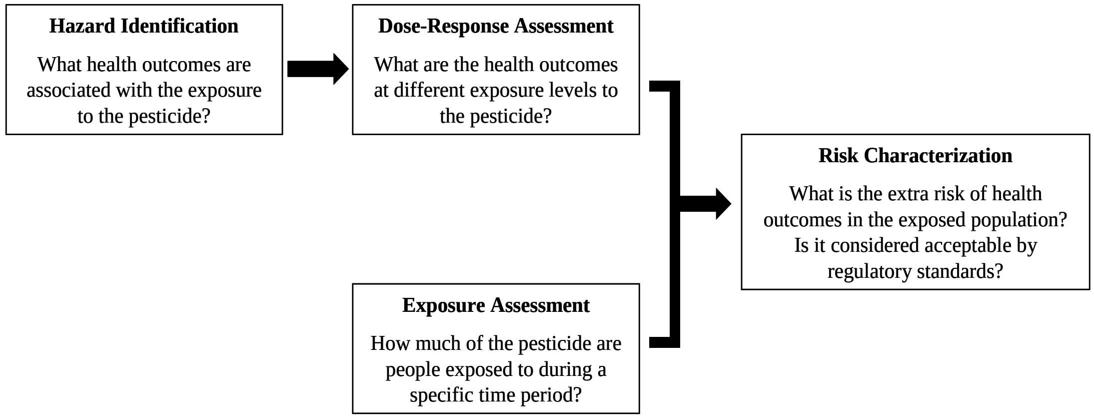


Figure 7-1: Description of the 4-Step Human Health Risk Assessment Process (USEPA, 2012)

7.1.3 Aim and Hypothesis

This Chapter addresses the fourth major aim of the current study's dissertation, which was to estimate the level of risk to the farmworkers, and their families, for developing cancer and non-cancer chronic health effects from residential exposure to agricultural pesticides. The major hypothesis is that the aggregate and cumulative risk assessments will show the risk of cancer and non-cancer chronic health effects to be acceptable in the farmworkers' homes, according to the present federally established guidelines for non-dietary ingestion of pesticides in yard soil and house dust, along with inhalation of pesticides in outdoor air.

7.2 Hazard Identification

7.2.1 Pyrethroids: the Hazards of Interest

The hazards of interest used for risk assessment in the current study were the agricultural pesticides of permethrin and bifenthrin, because these two pesticides were those detected at a relatively high detection frequency in all three sampled media (i.e., outdoor air, yard soil, and house dust). Permethrin and bifenthrin are both part of the pesticide family known as pyrethroids. Pyrethroids are synthetic insecticides based on the chemical structure of a natural insecticide group called pyrethrins, which are produced from the chrysanthemum flower (USEPA, 2013). The modes of action of pyrethroids and pyrethrins are very similar, but the synthetic pyrethroids have been modified to have greater environmental stability, particularly under UV-light conditions (ibid). Overall, pyrethroids are considered to be less toxic to humans compared to other types of insecticides (Dewailly et al., 2014), while more toxic to the targeted insects (Hwang et al., 2008). It is perhaps this generalized idea that pyrethroids and pyrethrins are safer and more effective than their alternatives that has led to a sharp increase in the use of these two pesticides throughout the United States in recent years (USEPA, 2013). In addition, regulatory changes to organophosphates (OPs), such as the discontinued residential registration of chlorpyrifos and diazinon, two of the most commonly applied OPs, has led a notable increase of pyrethroids on the market for both residential and agricultural purposes (USEPA, 2011b).

7.2.2 Health Effects Associated with Pyrethroids

Regardless of the cause of increased use of pyrethroids, there is still evidence that pyrethroids can cause chronic health effects. It is known that pyrethroids are able to cross the placental barrier (Dewailly et al., 2014) leading to reproductive and developmental concerns. Multiple studies in the peer-reviewed literature have reported developmental effects on the offspring of mothers exposed to pyrethroids

(Belle et al., 2001; Hanke et al., 2003), yet these results are conflicting with other studies reporting no evidence of developmental abnormalities (Dabrowski et al., 2003, Berkowitz et al., 2004). On the other hand, there is also research that supports the notion that bifenthrin, in particular, is an endocrine disruptor and can cause reproductive/developmental toxicity. For example, the Japanese medakas, a fish species, was found to have an increased expression of a precursor protein for estrogenic endocrine disruption upon exposure to a bifenthrin enantiomer (Wang, 2007). Additionally, in an older study, where rats were fed bifenthrin over the course of two generations, the first generation experienced less body weight gain (IPCS, 1992). Similarly, exposure to permethrin in rats has demonstrated oxidative stress and DNA damage associated with growth and development, such a motor deficits and memory dysfunction (Abdel-Rahman et al., 2002; Otitoju et al., 2008).

According to the USEPA, the pesticide bifenthrin is a possible human carcinogen, based on an in-house exposure study of mice that resulted in adenomas (benign tumors) and adenocarcinomas (malignant tumors) of the liver, bronchia, and bladder (USEPA, 2003a). Similarly, the pesticide permethrin has been classified by USEPA as “likely to be carcinogenic to humans” based on studies of mice and rats that demonstrated that oral ingestion of permethrin led to adenomas and carcinomas in the lung and liver (USEPA, 2009). Given that there is evidence that bifenthrin and permethrin are both associated with cancerous and non-cancerous outcomes, it was necessary in the current study to perform two different risk assessments to capture risk of chronic health effects for both types of pesticides.

Since permethrin and bifenthrin both belong to the pyrethroid family of pesticides, and thus the hazards presented by permethrin and bifenthrin create an additive effect. As such, in addition to an aggregate risk assessment, which quantifies risk associated with exposure to each pesticide separately, a cumulative risk assessment was performed, which quantifies risk associated with exposure to bifenthrin and permethrin in combination together.

7.2.3 Acute and Chronic Health Effects

The hazard identification step identifies which adverse health effects may potentially be caused by exposure to the chemical of interest. Health effects generally vary in response to acute versus chronic exposure. Acute exposures are those of an instantaneous or short duration, often caused by an accidental release of a hazardous agent. On the other hand, chronic exposures are generally defined as exposures that are longer than 10% of the human life (USEPA, 2011a). Chronic health effects, such as cancer or endocrine disruption, often do not surface for many years, making the risk assessment process particularly useful in predicting the level of risk an individual has of experiencing an adverse health effect in later years as a result of prolonged and repeated exposures (USEPA, 2012). For the risk assessment in the current study, chronic health effects were considered.

7.3 Dose-Response Assessment

7.3.1 Dose-Response Levels and Dose-Response Curves

The dose-response in the risk assessment step quantifies the level at which adverse health effect(s) can be observed. Risk assessors generally rely on, and incorporate into their risk assessments, the already existing dose-response data from previous studies that involve animals, human, or cell lines. However, it is possible to conduct one's own experiment to observe responses over a range of doses. Chemicals can follow dose-response curves that are either non-linear or linear (Figure 7-2). For non-cancer health effects, the chemical follows a non-linear dose-response curve, in which a threshold must be reached before an adverse effect is observed. For cancer, the chemical follows a linear dose-response curve, which has no threshold, and therefore assumes there is no level of exposure for that chemical which does not pose a probability of adverse health effect.

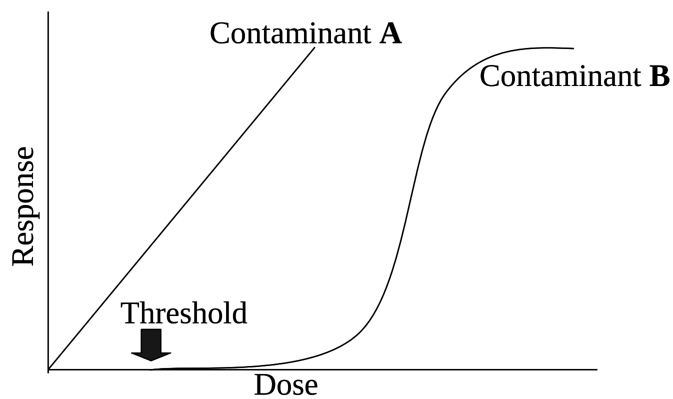


Figure 7-2: Depiction of Linear Dose-Response Curve (Contaminant A), Which Does Not Have a Threshold and Non-Linear Dose Response Curve (Contaminant B), Which Does Have a Threshold (DCBC, 2015).

7.3.2 Incorporation of Uncertainty Factors and Safety Factors

Dose-response assessors acknowledge that there are often limitations in the data being assessed, and for this reason, uncertainty factors (UF) and safety factors (SF) may be incorporated into the aggregate and cumulative risk assessments performed. UFs are used to adjust dose-response data by accounting for certain types of uncertainty. In general, the first UF is a 10-fold (10X) factor that takes into account variation in the susceptibility of adverse health effects among humans, otherwise known as "inter-individual variability." The next UF is another 10-fold (10X) factor that accounts for uncertainty when extrapolating data from an animal study and applying the data to humans, which is known as "intra-species variability." As a default, most chemicals, such as pesticides, are adjusted by 100X to incorporate both of the two uncertainties in the dose-assessment risk assessment. For some chemicals, there may be an additional three-fold (3X) UF when there is a lack of developmental neurotoxicity studies. In these cases, the chemical would be adjusted by a 300-fold factor (300X) to account for all three uncertainties. The Food Quality Protection Act (FQPA) safety factors (SF) include a 10-fold (10X) SF to provide added protection for pre and post-natal toxicity in cases where special sensitivity or exposure of infants and children is identified, along with a 10-fold (10X) SF when there is a lack of completeness of data with respect to exposure and toxicity to infants and children. FQPA safety factors are incorporated in the dose-response assessment to add an extra measure of protection for infants and children.

In cases where no increased sensitivity or exposure to these subgroups has been demonstrated and/or when there is reliable data to suggest that there is no increased sensitivity of exposure, the respective SFs are removed (i.e., become 1X) (USEPA, 2012). The USEPA has currently reduced the FQPA SF for pyrethroids to 1X for those greater than six years old, and has retained a 3X SF for children up to six years old (USEPA, 2011c).

7.3.3 Points of Departures

7.3.3.1 Non-Cancer Outcomes

A point of departure (POD) is a point on a chemical's dose-response curve that "departs" from the observed range of response data; the POD is an observed or extrapolated dose that usually approximates a "minimally toxic" response (USEPA, 2002b). The most common POD is of a chemical is the "no observed adverse effect level" (NOAEL), which is the highest exposure level at which the adverse health effect of concern is not observed, or the "lowest observed adverse effect level" (LOAEL), which is the lowest exposure level at which the adverse health effect of concern is observed. When the range of observation does not include sufficient data to identify the NOAEL and LOAEL, the risk assessor uses extrapolation to make inferences regarding at what dose level there may begin to be an adverse effect in humans (USEPA, 2012). For non-cancer risk assessments, the NOAEL is often used to compute a reference dose (RfD), which estimates the daily exposure level without an appreciable risk of chronic health effects over the lifetime. The RfD is computed by dividing the NOAEL by the relevant UFs. A toxicological level of concern (LOC) is also established. The LOC is equal to the UF, so this is most frequently 100, although this is not always the case.

Another POD is a benchmark dose (BMD), which is derived from modeling a dose-response curve and interpolating a dose estimate for a desired threshold response level (i.e., the response level is the benchmark). For cumulative risk assessments, which take into account multiple chemicals, BMDs can be used determine the relative potency factor (RPF), which establishes toxicity of a chemical in relation to an index chemical, in which the RPF for that index chemical is set to one. In order to compute the RPF, a desired benchmark dose (BMD) of both chemicals is taken into account. According to the USEPA's Guidance on Cumulative Risk Assessment of Pesticide Chemicals That Have a Common Mechanism of Toxicity (USEPA, 2002b), NOAELs/LOAELs can be used instead of BMDs if dose-response modeling is not available, but this is less desirable. The reason why NOAELs/LOAELs are less desirable for this purposes is the fact that these PODs do not always reflect the relationship between the dose and response for a chemical; in addition, NOAELs/LOAELs do not present a uniform response across multiple chemicals (ibid). It was further mentioned that an individual chemical's RfD should not be used to determine RPF values because RfDs are based on the most sensitive toxic effect among all of the toxicities produced by the chemical, yet that most sensitive effect may not be the same as the common toxic effect among a group of chemicals (ibid).

7.3.3.2 Cancer Outcome

For cancer, the most common POD is the lower bound (95^{th} % confidence limit) estimate of probability that the individual will develop cancer if exposed to the chemical for a lifetime. Usually the chemical's carcinogenic potential is estimated based on the linear slope cancer slope factor ($Q1^{*}$) can be estimated from the slope of the line from the lower bound to zero (Friis, 2012).

7.3.3.3 Dose-Response for the Current Study

For the current study, toxicological dose-response data for permethrin and bifenthrin were obtained from official documents released by the USEPA. Specifically, USEPA's final report on cumulative pyrethroid risk assessment (USEPA, 2011c) was referenced, along with the most updated Reregistration Eligibility Decision (RED) for additional data on permethrin (USEPA, 2009) and a *Federal Register* issue, the official federal government publication used to publish regulations and legal notices of government agencies and is made available monthly to the public (USEPA, 2003a) (Table 7-1).

Table 7-1: Toxicological Dose-Response Data for Permethrin and Bifenthrin

Dose-Response Variable	**Permethrin**[a,c]	**Bifenthrin**[b,c]
NOAEL (chronic dietary)	$25 \frac{mg}{kg{\cdot}day}$	$1.3 \frac{mg}{kg{\cdot}day}$
LOAEL	$75 \frac{mg}{kg{\cdot}day}$	$2.7 \frac{mg}{kg{\cdot}day}$
RfD (chronic oral)	$0.25 \frac{mg}{kg{\cdot}day}$	$0.004 \frac{mg}{kg{\cdot}day}$
LOC	100	300
Oral BMD_{20}	156.0	14.3
Oral RPF	1.0	10.9
$Q1^*$ (cancer slope factor)	9.6×10^{-3}	EPA recommends using RfD approach rather than assignment of $Q1^*$
UF (chronic dietary)	100X	300X
FQPA SF	3X for children ≤6 yrs; 1X for all other age groups	3X for children ≤6 yrs; 1X for all other age groups

[a]USEPA, 2009; [b]USEPA, 2003a; [c]USEPA, 2011a

For the current study, the BMD was used to determine RPFs. Permethrin was chosen as the index chemical because more thorough data related to its toxicity is availale compared to bifenthrin (ibid), and therefore its RPF was set to one.

In accordance with USEPA's cumulative risk assessment for pyrethroids (2011c), in the current study, a BMD_{20} was used to estimate the RPF (i.e., response level of 20%). In USEPA's risk assessment, the BMDs were modeled using a modeling average approach based on parametric bootstrapping from Wheeler and Bailer (2007), and a BMD_{20} was ultimately chosen because it was the most conservative estimate that was able to predict a significant change from the control values (USEPA, 2011c). Using a BMD_{20} value was also justified by the fact that previous studies focusing on pyrethroids also used a similar BMD threshold value (Wolansky et al., 2006; Raffaele et al., 2008).

The RPF for bifenthrin was calculated using Equation 7-1:

$$Equation\ 7-1: \quad RPF_{bifenthrin} = \frac{BMD_{20}^{permethrin}}{BMD_{20}^{bifenthrin}}$$

7.4 Exposure Assessment

7.4.1 Overview

The exposure assessment step seeks to understand the level of exposure incurred by the individual(s) to the hazard of interest. In most cases, exposure is not measured directly, but rather is estimated indirectly by taking into account the chemical concentration in the environment and estimating human intake (mg/kg/day) by each exposure route (e.g., ingestion, inhalation, dermal) over time. Since an exposure scenario often involves making multiple assumptions, such as ingestion or inhalation rate (mg/day or m^3/min/kg), exposure duration (min/day), exposure frequency (days/year), average time of exposure known as "averaging time" (day), and body weight (kg), determining exposures is considered to be the least understood component of the risk assessment process.

7.4.2 Exposure Assessment for the Current Study

For the current study, exposure scenarios were considered for the following age groups: 6 weeks-1 year, 1 year-<6 years, 3 years-<6 years, 6 years-<21 years, and ≥21 years. The soil and dust ingestion dose, $Dose_{sd}^{p}$ $(\frac{mg}{kg \cdot day})$, calculation used Equation 7-2.

$$Equation\ 7-2: \quad Dose_{sd}^{p} = \frac{C_{sd}^{p} \cdot CF \cdot IR_{sd}^{ingest} \cdot EF \cdot ET \cdot ED}{BW \cdot AT}$$

The air inhalation dose, $Dose_{a}^{p}$ $\left(\frac{mg}{kg \cdot day}\right)$, calculation used Equation 7-3.

$$Equation\ 7-3: \quad Dose_{a}^{p} = \frac{C_{a}^{p} \cdot IR_{a}^{inhale} \cdot EF \cdot ET \cdot ED}{AT}$$

One difference between the calculation of the $Dose_{sd}^{p}$ and $Dose_{a}^{p}$ for the cancer outcome versus the non-cancer outcome is that the "averaging time" of a non-carcinogen is equal to the exposure duration, while for cancer the "averaging time" is equal to the lifetime expectancy for a carcinogen. Also, for a non-carcinogen, exposure time is expressed as a unitless fraction of the day during which the person is exposed to the chemical, while for a carcinogen, exposure time is expressed in minutes per day. The variables used to compute exposure via ingestion and inhalation dose can be seen in Table 7-2. Note that a summary of the measured pesticide concentrations in the outdoor air, yard soil, and house dust can be found in Chapter 2 of this dissertation.

Table 7-2: Variables Used to Compute Exposure via Ingestion and Inhalation Dose

Variable	**Description**	**Units**
C_{sd}^{p}	Maximum concentration of pesticide detected in soil and dust	$\frac{\text{ng}}{\text{g}}$
C_{a}^{p}	Maximum concentration of pesticide detected in air	$\frac{\text{mg}}{\text{m}^3}$
CF	Conversion factor	$1\text{x}10^{-9}\ \frac{\text{g}}{\text{ng}}$
IR_{sd}^{ingest}	Intake rate of soil and dust via non-dietary ingestion	$\frac{\text{mg}}{\text{day}}$
IR_{a}^{inhale}	Inhalation rate of air per body weight	$\frac{\text{m}^3}{\text{min}\cdot\text{kg}}$
EF	Exposure frequency	$\frac{\text{days}}{\text{year}}$
ET	Exposure time	·Ingestion (unitless) $(\frac{\text{min}}{1{,}440\ \text{min in a day}})$ ·Inhalation $(\frac{\text{min}}{\text{day}})$
ED	Exposure duration	years
BW	Body weight	kg
AT	Averaging time ·carcinogen: AT= life expectancy ·non-carcinogen: AT= ED	days

For non-carcinogens, the calculated exposure dose is called an average daily dose (ADD) while the calculated exposure dose for carcinogens is called a lifetime average daily dose ($LADD$), but these doses are calculated the same way. Using Equation 7-4, the lifetime aggregate exposure dose for cancer, $LADD\left(\frac{mg}{kg\cdot day}\right)$, and the aggregate exposure dose for non-cancer outcomes, $ADD\left(\frac{mg}{kg\cdot day}\right)$, can both be calculated.

$$Equation\ 7-4: \quad LADD\ or\ ADD = Dose_{sd}^{p} + Dose_{a}^{p}$$

All exposure scenario assumptions in the current study were obtained from the 2011 Exposure Factors Handbook (USEPA, 2011a) or other standard default values determined by the USEPA (USEPA, 2015c). USEPA's reasonable maximum exposure (RME) approach was used, which assumes that exposures are from the 95th percentile of the exposure distribution, which is intended to capture exposures that are higher than average, yet still within a realistic range (USEPA, 2015c). A list of exposure scenario assumptions in the current study can be seen in Table 7-3.

Table 7-3: Variables and Methods Used for Exposure Scenario Assumptions

Variable	Method	Source
Body Weight (kg)	Used time weighted average equation (Equation 3-5) for overlapping age groups- necessary for all age groups except ages 3-<6	USEPA, 2011a (Table 8-1)
Ingestion Rate ($\frac{mg}{day}$)	Used soil and dust ingestion rate together; for ages 3-6 used general population upper percentile but for all other age groups used general population central tendency- based on what was available in the EFH	USEPA, 2011a (Table 5-1)
Inhalation rate ($\frac{m^3}{min \cdot kg}$)	Used 95th% values of recommended long-term exposure values for inhalation; males and females combined and divided by body weight for each age category; used TWA average$^+$ for overlapping years	USEPA, 2011a (Table 6-1)
Exposure duration ($years$)	Used 95th% for each child age group; Used 95th% from EFH, 2011 for adults	USEPA, 2011a USEPA, 2015c;
Exposure frequency ($\frac{days}{year}$)	Assumed standard default value of 350 days/year (on vacation for about 2 weeks)	USEPA, 2015c
Averaging time ($days$)	Non-carcinogen= ED(years)*365(days/year)- 95th% from each child age group and 95th% from EFH, 2011 for adults Carcinogen= 76(years)* 365(days/year)= 27740 days – based on life expectancy of 76 years	USEPA, 2011a USEPA, 201c5;
Exposure time ·Inhalation ($\frac{min}{day}$) ·Ingestion (unitless)	For outdoors: considered “Time spent at home in the yard or other areas outside the house”; for indoors: considered “Time spent in all rooms combined at home”; used TWA average for overlapping years; no value for 6 weeks-<1 year so divided value for 1-<6 year category in half; assumed life expectancy of 76 years and cut off “adult” at this age; to compute exposure time at home, added time at home outside and time at home inside	USEPA, 2011a, (Tables 16-16 and 16-20)

The time-weighted average for body weight, TWA_{bw} (kg), was computed using Equation 7-5.

$$Equation\ 7-5: \quad TWA_{bw} = \frac{\sum_{i=1}^{n} BW_i \cdot T_i}{\sum_{i=1}^{n} T_i}$$

Where: BW_i is body weight during ith interval and T_i is number of years in ith interval

7.5 Risk Characterization

7.5.1 Risk Characterization Approaches

Risk characterization consists of calculating the risk by a variety of methods, and making conclusions about the level of risk involved, and whether such risk is acceptable compared to a standard or guideline. The reliability of the risk characterization conclusions is contingent upon the soundness of the previous steps performed in the risk assessment. The final risk characterization incorporates the assumptions made, and takes into account relevant uncertainties. Risk characterization requires a risk assessor to use his or her judgment about both the presence and extent of the risk in question.

7.5.2Non-Cancer Risk

7.5.2.1 Calculating Margin of Exposure and Comparing to Level of Concern

There are several approaches that can be used to calculate risk. Particularly for cumulative risk assessments, there is more than one way to handle additivity of doses from multiple chemicals (Borack et al., 2008). For non-cancer outcomes, one method uses relative potency factors (RPF), in which the toxic potency of chemicals is scaled to that of an index chemical (ibid). For the RPF approach, it is necessary that the index chemical be well characterized from a toxicological perspective, and that it is known to be representative of all of the other chemicals in the mixture (ibid). The RPF approach was used in the current study's risk assessment because there is significant toxicological information available for both permethrin and bifenthrin.

For the aggregate non-cancer outcome risk assessment, the RPF was used to calculate a margin of exposure for the pesticides in the outdoor air, yard soil, and house dust ($MOE_{asd}^{p_i}$) (Equation 7-6), which was then compared to the level of concern (LOC), where an $MOE_{asd}^{p_i}$>LOC indicated an acceptable risk. The NOAEL was used, rather than the LOAEL, to compute the MOE, because using the former is a more protective approach.

$$Equation\ 7-6:\quad MOE_{asd}^{p_i} = \frac{NOAEL}{ADD\ \cdot RPF}$$

For the cumulative non-cancer outcome risk assessment, the sum of the margins of exposure ($SMOE_{asd}^{p_i}$) was calculated using Equation 7-7. A $SMOE_{asd}^{p_i}$>LOC indicated an acceptable risk.

$$Equation\ 7-7:\quad SMOE_{asd}^{p_i} = \sum MOE_{asd}^{p_i}$$

7.5.2.2 Calculating Hazard Quotient and Comparing to Standard Level of One

A second method to assess risk for non-cancer outcomes is the hazard quotient (HQ) approach, which combines the exposure level and toxicity of each chemical into a single value. For a cumulative risk assessment, the HQ of each chemical is added together into a single value with potency-weighted dose additions, called a hazard index (HI). This method is generally used when toxicological information regarding the chemicals is limited. In the current study, it was decided to additionally use the

HQ/HI method in the current risk assessment because the RPF method is usually used for mixtures that include many chemicals, but the current study's risk assessment only considered two pesticides (i.e., permethrin and bifenthrin). Using this approach for the aggregate risk assessment, a hazard quotient for each pesticide in the outdoor air, yard soil, and house dust ($HQ_{asd}^{p_i}$) was computed using Equation 7-8. If $HQ_{asd}^{p_i}$ <1, then the risk was considered to be acceptable.

$$Equation\ 7-8: \quad HQ_{asd}^{p_i} = \frac{ADD}{RfD}$$

In determining the cumulative risk for non-cancer outcomes, a hazard index of permethrin and bifenthrin combined in the outdoor air, yard soil, and house dust ($HI_{asd}^{p_i}$) was computed using Equation 3-9. If $HI_{asd}^{p_i} < 1$, then the risk was considered to be acceptable.

$$Equation\ 3-9: \ HI_{asd}^{p_i} = \sum HQ_{asd}^{p_i}$$

7.5.3 Cancer Risk

7.5.3.1 Calculating Individual Excess Lifetime Cancer Risk and Comparing to One-in One-Million Cancer Risk

For the cancer outcome, the most common approach is to calculate the individual excess lifetime cancer risk ($IELCR_{asd}^{p_i}$) by combining the dose and cancer slope factor. For the current study's aggregate risk assessment, Equation 7-10 was used to calculate $IELCR_{asd}^{p_i}$. The standard acceptable risk in the United States for cancer is one-in-one-million (1x10^{-6}).

$$Equation\ 7-10: \quad IELCR_{asd}^{p_i} = LADD \cdot Q1^*$$

For the cancer outcome cumulative risk assessment the sum of the individual excess lifetime cancer risks, $SIELCR_{asd}^{p_i}$, were calculated using Equation 3-11.

$$Equation\ 7-11: \quad SIELCR_{asd}^{p_i} = \sum IELCR_{asd}^{p_i}$$

7.5.3.2 Calculating "One Hit" Cancer Risk and Comparing to One-in One-Million Cancer Risk

A second approach was included, called the "one-hit model," which assumes that there is a single stage for cancer and one molecular incident induces cell transformation. The "one-hit model," though less realistic, was also included because it is the most protective approach. The risk of cancer for the aggregate risk assessment from "one-hit" ($Risk_{one-hit}{}_{asd}^{p_i}$) was calculated using Equation 3-12.

$$Equation\ 7-12: \quad Risk_{one-hit}{}_{asd}^{p_i} = 1 - e^{(Intake \cdot Q1^*)}$$

For the cumulative cancer outcome risk assessment, Equation 3-13 was used.

$$Equation\ 7-13: \quad SRisk_{one-hit}{}^{p_i}_{asd} = \sum Risk_{one-hit}{}^{p_i}_{asd}$$

In the "one-hit model" for both the aggregate and cumulative risk assessments, the calculated risks were again compared to the standard acceptable risk in the United States for cancer of one-in-one-million ($1x10^{-6}$).

7.5.4 Risk Characterization Results

7.5.4.1 Aggregate Non-Cancer Risk Characterization Results

The current study's results for non-cancer risk for the aggregate risk assessment can be seen in Table 7-4. For the aggregate risk assessments, the hazard quotients were many orders of magnitude lower than one, and the margins of exposure were several orders of magnitude greater than the level of concern for both bifenthrin and permethrin.

Table 7-4: Aggregate Risk Assessment Results for Non-Cancer Outcomes using Hazard Quotients and Margins of Exposure

Pesticide	Age Group	ADD ($\frac{mg}{kg \cdot day}$)	HQ	< 1	MOE	MOE> LOC#
Bifenthrin	6 wks-<1 yr	1.57×10^{-5}	6.27×10^{-8}	Yes	8.29×10^{4}	Yes
	1-<6 yr	1.27×10^{-5}	5.07×10^{-8}	Yes	1.03×10^{5}	Yes
	3-<6yr	1.96×10^{-5}	7.84×10^{-8}	Yes	6.63×10^{4}	Yes
	6-<21 yr	3.78×10^{-6}	1.51×10^{-8}	Yes	3.44×10^{5}	Yes
	≥21 yr	1.80×10^{-6}	7.18×10^{-9}	Yes	7.24×10^{5}	Yes
Permethrin (cis and trans isomers)	6 wks-<1 yr	3.38×10^{-5}	5.51×10^{-5}	Yes	7.39×10^{5}	Yes
	1-<6 yr	2.69×10^{-5}	4.38×10^{-5}	Yes	9.31×10^{5}	Yes
	3-<6yr	4.46×10^{-5}	7.24×10^{-5}	Yes	5.61×10^{5}	Yes
	6-<21 yr	7.49×10^{-6}	1.22×10^{-5}	Yes	3.34×10^{6}	Yes
	≥21 yr	3.08×10^{-6}	5.08×10^{-6}	Yes	8.12×10^{6}	Yes

#LOC=300 for bifenthrin, LOC=100 for permethrin

7.5.4.2 Cumulative Non-Cancer Risk Characterization Results

Results for non-cancer risk for the cumulative risk assessment can be seen in Table 7-5. For the cumulative risk assessments, the hazard indexes were all far below one and the margins of exposure were much greater than the level of concern.

Table 7-5: Cumulative Risk Assessment Results for Non-Cancer Outcomes using Hazard Indexes and Margins of Exposure

Pesticides	**Age Group**	**ADD** $(\frac{mg}{kg \cdot day})$	**HI**	**< 1**	**MOE**	**MOE> LOC#**
Bifenthrin & Permethrin (cis and trans isomers)	6 wks-<1 yr	4.95×10^{-5}	1.35×10^{-4}	Yes	7.47×10^{5}	Yes
	1-<6 yr	3.96×10^{-5}	1.07×10^{-4}	Yes	9.40×10^{5}	Yes
	3-<6yr	6.42×10^{-5}	1.78×10^{-4}	Yes	5.67×10^{5}	Yes
	6-<21 yr	1.13×10^{-6}	3.00×10^{-5}	Yes	3.37×10^{6}	Yes
	≥21 yr	4.88×10^{-6}	1.23×10^{-5}	Yes	8.19×10^{6}	Yes

#LOC=300 for bifenthrin, LOC=100 for permethrin

7.5.4.3 Aggregate Cancer Risk Characterization Results

Results for cancer risk for the aggregate risk assessment can be seen in Table 7-6. For both bifenthrin and permethrin, the incremental excess lifetime cancer risk from aggregate exposures were several orders of magnitude lower than one-in-one-million acceptable risk level, for all age groups. Likewise, the one-hit cancer risk from aggregate exposure was also below one-in-one-million acceptable risk level in all age groups for both bifenthrin and permethrin.

Table 7-6: Aggregate Risk Assessment Results for Cancer Outcome using Incremental Excess Lifetime and One-Hit Cancer Risks

Pesticide	Age Group	LADD	IELCR	Less than $1x10^{-6}$	One-hit Cancer Risk	Less than $1x10^{-6}$
Bifenthrin	6 wks-<1 yr	1.9×10^{-7}	7.84×10^{-10}	Yes	7.84×10^{-10}	Yes
	1-<6 yr	9.5×10^{-7}	3.79×10^{-9}	Yes	3.80×10^{-10}	Yes
	3-<6yr	1.47×10^{-6}	5.88×10^{-9}	Yes	5.88×10^{-9}	Yes
	6-<21 yr	9.92×10^{-7}	3.97×10^{-9}	Yes	3.97×10^{-9}	Yes
	≥21 yr	1.09×10^{-6}	4.35×10^{-9}	Yes	4.35×10^{-9}	Yes
Permethrin (cis and trans isomers)	6 wks-<1 yr	4.45×10^{-7}	4.79×10^{-9}	Yes	1.74×10^{-9}	Yes
	1-<6 yr	2.12×10^{-6}	2.04×10^{-8}	Yes	8.30×10^{-9}	Yes
	3-<6yr	3.52×10^{-6}	3.38×10^{-8}	Yes	1.37×10^{-8}	Yes
	6-<21 yr	2.07×10^{-6}	1.99×10^{-8}	Yes	8.12×10^{-9}	Yes
	≥21 yr	1.86×10^{-6}	1.79×10^{-8}	Yes	7.38×10^{-9}	Yes

7.5.4.4 Cumulative Cancer Risk Characterization Results

Results for cancer risk for the cumulative risk assessment can be seen in Table 7-7. The sum of incremental excess lifetime cancer risk were several orders of magnitude lower than the one-in-one-million acceptable risk level, for all age groups. Likewise, the one-hit cancer risks were also all below the one-in-one-million acceptable risk level for all age groups.

Table 7-7: Cumulative Risk Assessment Results for Cancer Outcome using Incremental Excess Lifetime and One-Hit Cancer Risks

Pesticides	Age Group	LADD	IELCR	Less than $1x10^{-6}$	One-hit Cancer Risk	Less than $1x10^{-6}$
Bifenthrin & Permethrin (cis and trans isomers)	6 wks-<1 yr	6.19×10^{-7}	4.84×10^{-9}	yes	4.84×10^{-9}	yes
	1-<6 yr	2.96×10^{-6}	2.31×10^{-8}	yes	2.31×10^{-8}	yes
	3-<6yr	4.81×10^{-6}	3.80×10^{-8}	yes	3.79×10^{-8}	yes
	6-<21 yr	2.96×10^{-6}	2.28×10^{-8}	yes	2.28×10^{-8}	yes
	>21 yr	2.95×10^{-6}	2.22×10^{-8}	yes	2.22×10^{-8}	yes

7.5.5 Risk Characterization Discussion

7.5.5.1 Overview

In the current study, both the aggregate and cumulative risk assessments were conducted to determine the level of risk to the farmworker and their families for cancer and non-cancer chronic health effects from non-dietary ingestion of the soil and house dust contaminated with agricultural pesticides, along with inhalation of the outdoor air for the agricultural pesticides detected in this study. The results of these risk assessments showed that the exposure to bifenthrin and permethrin, for both cancer and non-cancer outcomes, appear to be an acceptable level. The results of these risk assessments confirm the fourth major hypothesis of this dissertation.

7.5.5.2 Comparing Results to Other Studies in the Peer-Reviewed Literature

The results of the current study's non-cancer risk assessments are comparable to the USEPA's pyrethrins/pyrethroid cumulative risk assessment (USEPA, 2011c). In that risk assessment, 30 pyrethrins/pyrethroids were considered in a risk assessment that took into account multiple sources and routes of exposure in a deterministic manner. Residential exposures through non-dietary ingestion, dermal absorption, and inhalation, along with dietary exposure from dietary ingestion of food and drinking water were considered. The USEPA concluded that cumulative estimated risks from pyrethrins/pyrethroids were not concerning. The risk assessments in the current study for non-cancer outcomes are also comparable to the risk assessment done by Quirós-Alcalá et al., (2011), where house dust was sampled from homes of agricultural and non-agricultural families, and bifenthrin and permethrin were both targeted for analysis. Quirós-Alcalá et al. (2011) reported that the maximum hazard quotient estimated for children across the agricultural and non-agricultural populations were ~$1x10^{-6}$ - $1x10^{-2}$, which was considered an acceptable risk level. The results of the current study's risk assessments are within the range reported by Quirós-Alcalá et al. (2011).

Comparing the measured agricultural pesticide levels in the current study to those in other studies in the peer-reviewed literature, among both agricultural and non-agricultural populations, may provide further insight into whether the farmworkers in the current study experienced a markedly increased exposure risk compared to other populations. Given that it is well known that pesticides are ubiquitous in the environment, it is wise not to assume that the farmworkers of this study are exposed to agricultural pesticides at any level higher than that of an expected background level. Overall, the results of the current study were compared to a variety of agricultural and non-agricultural communities pesticide sampling studies that also sampled house dust (Table 7-8 and Table 7-9) or indoor/outdoor air (Table 7-10 and Table 7-11). Fourteen studies from the peer-reviewed literature were used for house dust comparisons. Permethrin has been widely targeted in the previous studies, and all 14 of the studies included reported permethrin levels in house dust. However, bifenthrin has not been as widely targeted in previous pesticide sampling studies, and only four of the studies reported house dust concentrations of this pesticide. Of the 14 studies, four studies sampled homes of an agricultural population, nine sampled homes of a non-agricultural community, and one sampled homes in both an agricultural and non-agricultural community.

The median value for permethrin in the sampled house dust of the current study (526 ng/g) was comparable to the median across all of the 14 considered studies (809 ng/g) (Table 7-9). The maximum value for permethrin (5,400 ng/g) was an order of magnitude lower in the current study than the value across all considered studies (29,530 ng/g). For permethrin, there was almost no difference in the median or maximum values in the house dust between the agricultural populations and the non-agricultural populations. For bifenthrin in the house dust, the median level was non-detectable (ND) in the current study compared to the level across the 14 considered studies (104 ng/g). On the other hand, the maximum house dust level of bifenthrin in the current study (2,241 ng/g) was much higher than the maximum across the peer-reviewed studies (30 ng/g). This may suggest that the farmworkers in the current study could have been exposed to higher levels of bifenthrin compared to other agricultural or non-agricultural populations. On the other hand, based on the full percentile distribution of bifenthrin concentrations in the sampled house dust (see Table 2-2) it appears that the maximum level of bifenthrin detected may be an outlier. Therefore, it is not possible to provide any strong assertions about how bifenthrin in the house dust for the current study compares to other studies. Nonetheless, it can be seen that bifenthrin levels across non-agricultural populations in peer-reviewed studies were slightly higher than, but still comparable to, the agricultural population tested in the current study.

Permethrin in the air was very similar in the current study compared to the peer-reviewed studies for both the median (ND in the current study versus 5 ng/m^3 across the peer-reviewed studies) and maximum (2 ng/m^3 versus 10 ng/ m^3).

Permethrin in the air was also similar to the studies in agricultural populations versus non-agricultural populations for both the median (ND versus 5 ng/m^3) and maximum (6.5 ng/m^3 versus 12 ng/m^3) (Table 7-10). Likewise, bifenthrin in the outdoor air, for the current study, was comparable to the levels across the peer-reviewed studies, having the same median values (ND) and maximum values (4 ng/m^3). Bifenthrin in the outdoor air was also similar for the studies in agricultural populations versus non-agricultural populations for the median (ND for both) and maximum (34 ng/m^3 versus 3 ng/m^3) (Table 7-11). Overall, the results of the peer-reviewed literature suggest that the farmworkers, and their families, in the current study are exposed to permethrin and bifenthrin in the house dust and outdoor air at levels comparable to other study populations in both agricultural and non-agricultural communities.

7.5.5.3 Exercising Caution When Making Conclusions Related to Risk Assessments

Although the risk assessments performed in the current study may suggest that the particular exposures to bifenthrin and permethrin alone were not of concern for cancer or other chronic health effects, it would be unwise to hastily assume that agricultural pesticide exposure is not a health hazard in Yuma County, Arizona.

First, it must be remembered that risk assessments are highly embedded in assumptions. For example, while the dose-response assessment takes uncertainties into account, the uncertainty/safety factors are limited in that they are dichotomous variables (i.e., either they are applied at a standard level or not applied at all). In addition, the development of potential exposure scenarios includes multiple assumptions, but without direct observation of behaviors in the population of interest, the exposure assessment is limited to national averages and general guidelines. Next, samples in the current study could target a limited number of pesticides because of the high costs of analysis. According to the Arizona Department of Agriculture 1080 Pesticide Application Database, 157 different types of agricultural pesticides were applied in Yuma County over the sampling period of the current study (AZDA, 2014). As such, the pesticides that could be assessed in this risk assessment captured only approximately 1% of the agricultural pesticides applied in the agricultural community during the sampling period. This illustrates that although the tested bifenthrin and permethrin were within the acceptable risk levels, a risk assessment that captures all the agricultural pesticides applied in the community during the sampling period is outside of the scope of the current study.

In addition, there are other sources of potential exposure to agricultural pesticides such as via dietary ingestion of food and drinks, which was not captured in the current risk assessments. In fact, the primary route of agricultural pesticide exposure to the general population is through dietary ingestion of food and drink (Wilson et al., 2003; Bouvier et al., 2005; Lu et al., 2008). Residential use of pesticides is another source of exposure that was not incorporated into the current risk assessments, although this source may have been captured in the samples collected for homes where residential pesticide use did occur. As shown previously, residential pesticide use can result in at-home pesticide levels that are comparable to homes in agricultural communities (Rudel et al., 2003; Berger-Preiss et al., 2002; Julien et al., 2008; Morgan, 2012; Blanchard et al., 2014). Since the current study consisted of farmworker families, occupational pesticide exposure while working in the field would be an additional source of exposure for the farmworker(s) of the family. It is recommended that residential pesticide exposure of agricultural pesticides transported from nearby fields be incorporated into future cumulative risk assessments performed by federal regulators in order to better capture the total risk of populations in agricultural communities.

7.6 Conclusions

It is crucial to emphasize that the risk from agricultural pesticide exposures quantified in the current risk assessments are in addition to other pesticide exposures, including residential pesticide use, dietary ingestion, and occupational exposure while working in the field. In conclusion, the risk assessment results for bifenthrin and permethrin in the current study suggest an optimistic outlook on the potential exposure of farmworker families to these specific agricultural pesticides through non-dietary ingestion of yard soil and house dust, along with inhalation of outdoor air. However, caution should be exercised, since this risk characterization does not assert that agricultural pesticide exposure is not of health concern to this study’s population.

Table 7-8: Results of Studies that Targeted Permethrin and Bifenthrin for Analysis in House Dust Samples (ng/g) in Agricultural and Non-Agricultural Populations

Study Location; Time Period	**Ag**	**N**	**cis-Permethrin (ng/g)**			**trans-Permethrin**			**Permethrin (cis +trans)**			***Bifenthrin***		
			DF	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*
[a] AZ; 2011-12	Y	21	91	233	2,208	100	568	6300	91	801	5,400	10	ND	2,241
[b] CA; 2009	Y	55	67	244	1,410	67	172	1,737	67	416	3147			
[c] CA; 2009	Y	85	100	666	14,122	100	711	11,980	100	1,377	14,833			
[d] CA; 2000-02	Y	504	98	344	168,000	98	467	265,000	98	811	433,000			
[e] CA; 2002	Y	20	100	150	2,900	100	230	5,800	100	380	8,700	5	ND	30
[f] CA; 2006	Y	15	100	568	6,300	100	952	9,690	100	1,520	15,990	14	ND	23.9
	N	13	100	291	26,700	100	504	46,800	100	795	73,500	8	104	116
[g] France; 2010-11	N	25							84	550	36,700			
[h] MA; 2002-03	N	35							100	920	13100	3	ND	10
[i] CA; 2004	N	11	91	52	319*	91	126	680*	91		999*			
[j] NC & OH; 2000-01	N	118							100	344				
[k] MI, IA, CA, WA; 1999-01	N	513	72	337$^{\wedge}$		74	517$^{\wedge}$		74	854$^{\wedge}$				
[l] MA; 1999-01	N	119	53	ND	61,900	67	387	98,000	67	387	159,900			
[m] Germany; 1996-99	N	61							94	1,200	5,900*			
[n] Germany; 1996-98	N	2340							75	9,650	659,190			
[o] NC; 1996	N	25		12,080^{+}				17,450^{+}						

Ag= agricultural population (Yes/No); N=sample size; DF= detection frequency (%); p50=50th %; ND= not detectable; *90th or 95th percentile reported; $^{\wedge}$geometric mean reported; $^{+}$arithmetic mean reported

[a]Current study; [b]Trunelle et al., 2011; [c]Starr et al., 2008; [d]Harnly et al., 2009; [e]Bradman et al., 2007; [f]Quirós-Alcalá et al., 2011; [g]Blanchard et al., 2013; [h]Julien et al., 2008; [i]Hwang et al., 2008; [j]Morgan, 2012; [k]Colt et al., 2004; [l]Rudel et al., 2003; [m]Leng et al., 2005; [n]Berger-Preiss° et al., 2002;[o]Lewis et al., 1999

Table 7-9: Comparison of Current Study to Summarized Median Values of Detection Frequency and Pesticide Concentrations in House Dust (ng/g) from Previous Studies

Population Type	cis-Permethrin			trans-Permethrin			Permethrin (cis +trans)			Bifenthrin		
	DF	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*
[a]AZ; 2011-12	91	233	2,208	100	568	6,300	91	801	5,400	10	ND	2,241
Agricultural	99	294	4600	100	518	7,995	99	806	11,767	6	ND	30
Non-agricultural	82	314	44300	83	446	32,125	91	825	36,700	10	104	63
Overall	99	316	16500	99	486	13570	98	809	29,530	6	104	30

[a]Current study

Table 7-10: Results of Studies that Targeted Permethrin and Bifenthrin for Analysis in Household Air Samples (ng/m^3) In Agricultural and Non-Agricultural Populations

Study Location & Time Period	**Ag**	**N**	**I/O Air**	**cis-Permethrin**			**trans-Permethrin**			**Permethrin (cis +trans)**			**Bifenthrin**		
				DF	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*
[a] Yuma; 2011-12	Y	21	O	5	ND	1	19	ND	1	19	ND	2	43	ND	4
[b] CA; 2002	Y	20	I	40	ND	8	16	ND	11	40	ND	11	5	ND	63
			O	39	ND	8	0	ND	ND	39	ND	8	5	ND	ND
[c] France 2010-11	N	30	I							0	ND	ND			
[d] MA; 2010-2011	N	20	I							5	ND	3			
[e] FL; 2001	N	9	I	89	2.0	92	89	3	130	89	5	222	11	ND	3
			O	100	2.1	2	100	3	10	100	5	12	0	ND	ND
[f] NC & OH; 2000-01	N	118	I	125							21	ND			
			O	127							18	ND			
[g] MA; 1999-2001	N	120	I	3	ND	4	3	ND	5	3	ND	9			
[h] Germany; 1996-99	N	2,340	I							67	2	14			
[I] Germany; 1996-99	N	61	I							41	ND	23			

Ag = agricultural population; N=sample size; I/O= indoor/outdoor air sampled; ND= not detectable
[a]Current study; [b]Bradman et al., 2007; [c]Blanchard et al., 2013; [d]Lu et al., 2013; [e]Tulve et al., 2008; ; [f]Morgan, 2012; [g]Rudel et al., 2003; [h]Berger-Preiss° et al., 2002; [i]Leng et al., 2005

Table 7-11: Comparison of Current Study to Summarized Median Values of Detection Frequency and Pesticide Concentrations in Indoor and/or Outdoor Air (ng/m$^{3)}$ of from Previous Studies

Population Type	**cis-Permethrin**			**trans-Permethrin**			**Permethrin (cis +trans)**			**Bifenthrin**		
	DF	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*	*DF*	*p50*	*Max*
[a] AZ; 2011-12	5	ND	1	19	ND	1	19	ND	2	43	ND	4
Agricultural	22.5	ND	4.5	17.5	ND	6	29.5	ND	6.5	24	ND	33.5
Non-agricultural	100	2.05	4	89	3	10	36	5	12	5.5	ND	3
Overall	64.5	2.05	6	17.5	3	10	39	5	10	5	ND	4

[a]Current study

CHAPTER 8

DISSERTATION CONCLUSIONS

8.1 Major Findings and Contributions

Past intervention studies attempting to reduce agriculture pesticides in farmworker homes have mainly focused on altering the take-home/soil track-in pathway and the related risk factors inherent in the behaviors of the farmworkers. Such a narrow focus has resulted in limited success in reducing the presence of agriculture pesticides in the homes of farmworkers and their families. In the current study, the take-home/soil track-in pathway of agricultural pesticides into farmworkers' homes was still considered, but the air infiltration pathway was also explored more extensively than it generally has been in past studies. In addition, the residence time of the respective pesticides were quantified and discussed.

Furthermore, household-level risk factors, as well as risk factors that are external to the farmworkers and their household, were explored in order to broaden the understanding of potential predictors of agricultural pesticide levels in farmworkers' homes. The major findings and contributions of this dissertation to the fields of environmental health and public health are as follows:

Quantification of pesticide levels in indoor and outdoor media

The sampling in this dissertation's study included both indoor media (house dust) and outdoor media (yard soil and air). This was unique compared to the majority of prior similar studies, which mostly only sampled the farmworkers' house dust. The expanded sampling provided insight into the levels of agricultural pesticides immediately outside the home compared to those inside the home, helping to shed light on potential transport pathways of agricultural pesticides into the homes.

Application of a pesticide hazard ranking system

Previous researchers have tended to be repetitive in the agricultural pesticides they targeted despite the fact that the pesticides applied are continually evolving. Before the sampling began for the current study, the application of a previously developed pesticide hazard ranking system (Sugeng, 2012; Sugeng et al., 2013) was used to enable the targeting of a limited suite of sampled agricultural pesticides. Use of the hazard ranking system is recommended to assist future pesticide researchers in identifying which pesticide hazards are most relevant to their community of interest at that time. The advantages of using that system before sampling began were two-fold.

***A more cost efficient pesticide sampling was conducted* -** Since field sampling is costly, time-consuming, and resource intensive, it is important that a strategic sampling and analysis plan be developed before sampling is begun. One of the challenges in field sampling is how to decide which pesticides to target when a great number of pesticides are being applied in the community of interest. The savings afforded by the use of the hazard ranking system in the current study is evidenced by the fact that: all of the pesticides identified by the hazard ranking system were detected in at least one media for any given household; two of the pesticides, bifenthrin and cis/trans-permethrin, could be detected in all three media;

and one of the pesticides, trifluralin, was highly detected in the air although it was mainly undetected in soil and dust.

***Only relevant agriculture pesticides were targeted* -** The majority of the pesticides chosen for the current study were less commonly targeted in the 19 previous agricultural pesticide sampling studies (Simcox et al., 1995; Bradman et al., 1996; Robertson et al., 1999; Lu et al., 2000; O'Rourke et al., 2000; McCauley et al., 2001; Shalat et al., 2003; Thompson et al., 2003; Curwin et al., 2005; Thompson et al., 2005; Ward et al., 2006; Weppner et al., 2006; Bradman et al., 2007; Harnly et al., 2009; Gunier et al., 2011; Quirós-Alcalá et al., 2011; Golla et al., 2012; Lozier et al., 2012; Armstrong et al., 2013). Without the application of a hazard ranking system, most of the pesticides targeted in the current study would likely not have been chosen for analyses. For example, pronamide was not targeted in any of the previous studies. Bifenthrin, trifluralin, and endosulfan were each included in two of the previous studies. Permethrin and carbaryl were included in only four of the previous studies. Therefore, as a result of using the pesticide ranking system, more current and relevant applied pesticides were chosen.

Development, evaluation, and application of a pesticide transport model

***Quantified relative contributions of both soil and air pathways* -** In the current study, a pesticide transport modeling framework was developed, evaluated, and applied in order to quantify the relative contributions of both the take-home/soil track-in and air infiltration pathways. By application of the pesticide transport model, the current study showed that both air infiltration and soil track-in contribute to agricultural pesticide levels in the house dust, and in some cases, air infiltration comprises the vast majority of contribution to agricultural pesticide contamination in the house dust levels. Future researchers may be able to use the pesticide transport model to quantify the relative contributions of the air infiltration and soil track-in pathways, as well as calculate residence time of alternative pesticides, or even other semi-volatile organic compounds, into the house dust.

The current study explored possible reasons as to why a major previous intervention had limited success in reducing agricultural pesticide levels in the house dust of farmworkers' homes (Thompson et al. 2008; Strong et al., 2009). That intervention targeted the take-home/soil track-in pathway by trying to change farmworkers' behaviors, and then conducted follow-up testing four years after the baseline testing. In the current study, the respective median contributions of air infiltration and soil track-in for bifenthrin was 95.68%/4.31%, while for permethrin it was 42.13%/57.87%, respectively. These results suggest that the limited successes in the previous intervention may have been due to the interventions focusing on only one pesticide transport pathway (i.e., soil track-in). Both pathways may be relevant, but that relative contributions vary depending on the pesticide. In the current study, the pesticide transport model showed that the computed median residence time was five days for bifenthrin and 27 days for permethrin, which are both far below the four-year time period between baseline and follow-up testing of the previously mentioned intervention study. Therefore, follow-up testing after four years does not appear to be a major reason why the previous intervention was unable to reduce pesticide levels in the house dust.

Focused on pesticides adhered to soil particles - Prior to the current study, most research related to air transport of pesticides focused on spray drift (Richards et al., 2001; Quandt et al., 2004; Weppner et al., 2006). In the current study, the developed pesticide transport model included a focus on adherence to soil particles. This filled the data gap related to the relevance of wind resuspension of contaminated soil particles on air transport, and subsequently, air infiltration.

Exploration of pesticide external risk factors to farmworkers and families

The current study combined agricultural pesticide sampling in farmworkers' homes, together with the exploration of various pesticide risk factors that are external and uncontrollable by the farmworkers and their households. Previously, studies have shown that chemicals, including pesticides, can be influenced by their intrinsic chemical characteristics, microclimate/local weather conditions during sampling, and the spatial and temporal distribution of the chemical's application in the environment (Akesson and Yates, 1964; Bache and Johnstone, 1992; Wauchope et al., 1992; Gunier et al., 2001; De la Rosa et al., 2004; Ares et al., 2006; MacKay et al., 2006; Posen et al. 2006; USEPA 2014b).

Considered chemical characteristics of pesticide - The results of the current study found that chemical characteristics (ATSDR, 2003; Krieger and Kriege, 2001; MacKay et al., 1997; Hayes and Lewis, 1991, WHO, 2011) can be useful in understanding why certain pesticides were detected more frequently than others in certain media, particularly when there is a chemical characteristic that stands out for a pesticide or a group of pesticides. For example, the high vapor pressure of trifluralin suggested high partitioning in the gas phase, explaining its high detection frequency in the sampled air and almost non-existent detection frequency in soil and dust. The lower vapor pressure of bifenthrin, yet significant detection frequency in air (along with soil and dust), suggests that this pesticide mostly adhered to soil particles, and therefore, detection in the air was largely a result of re-suspended contaminated soil particles.

Considered microclimate/weather conditions during sampling period - In the current study, exploring the microclimate/weather conditions during the time of sampling (NWS 2014) helped shed light on factors driving pesticide concentrations in outdoor air. Although these conditions were not as effective for explaining the yard soil and house dust pesticide levels, this is likely explained by fact that air sampling was performed over 48 hours, whereas soil and dust sampling was a single collection, each of which only took a few minutes. The results of the current study showed: humidity and rain were negatively correlated with bifenthrin air concentrations, which is an expected finding for pesticides largely in the particle phase; average temperature was positively correlated with bifenthrin air concentrations, which is consistent with the drying of soil particles that promote wind-driven particles into the air; humidity and rain were positively correlated with trifluralin air concentrations, an expected finding for pesticides that are easily volatilized; and average temperature was negatively correlated with trifluralin air concentrations, which is likely to be a result of hindered volatilization upon hotter weather conditions. Unfortunately, the relationship between permethrin in outdoor air and microclimate/weather conditions could not be assessed because of its low detection frequency in outdoor air samples.

Considered pesticide applications within spatial and temporal buffers - The spatial and temporal distributions of the agricultural pesticide applications (AZDA 2014) were strongly associated with pesticide concentrations in the outdoor air at the farmworkers' homes. Testing the relationship between pesticide levels detected at homes and field applications of agricultural pesticides within multiple spatial and temporal buffers provided valuable insight into how alternative buffers can be more appropriate for different pesticides. The current study's results showed that: for bifenthrin, the one-mile and one-month spatial buffer was the most effective for predict association with pesticides at farmworkers' homes; for permethrin, agricultural applications throughout Yuma County one-month prior to sampling showed the strongest association with levels at farmworkers' homes; and for trifluralin, applications in the one-mile and one-year buffer were most strongly associated with outdoor air concentrations at farmworkers' homes. The current study highlights the advantage of including multiple spatial and temporal buffers, and shows the variability of results between optimal and less optimal buffers.

Widened exploration of pesticide household level risk factors

The onus of preventing pesticide transport into farmworkers' homes has primarily fallen on the family itself, yet the exploration of household-level factors which may influence agricultural pesticide levels in the house dust has been limited. The current study widened the number and type of household-level factors generally considered and tested for their association with agricultural pesticides levels at the farmworkers' homes. The household-level factors were categorized as follows:

household member characteristics, household behaviors, and housing structure characteristics. Overall, factors related specifically to the farmworkers, and their behaviors, were not among the strongest associations with bifenthrin or permethrin concentrations in the house dust, although certain farmworker behaviors did have some influence on bifenthrin levels. Considering contributions from all of the household residents and their behaviors, along with factors related to the structure of the house, helped to better capture the influential household-level factors on agricultural pesticides in the house dust. Being able to effectively clean the house was also found to highly influence pesticide detection in the house dust.

Highlighted discrepancies in participant-reported information - In the current study, most families perceived that they lived further away from an agricultural field than they actually did as measured by the researcher using GoogleEarth® (Google Inc., 2015) suggesting that certain farmworkers may consider agricultural pesticides to be only an occupational hazard, and they may not actively be thinking of agriculture pesticides as a residential hazard. Accordingly, it is possible that there were shortcomings in their awareness of potential transport into their homes by just living near an agricultural field.

Quantified relationship of home to nearest field distance - For bifenthrin, the measured distance from the home to the nearest agricultural field was negatively associated with bifenthrin in house dust, supporting the idea that bifenthrin levels are strongly related to living in an agricultural community, rather than only due to the farmworker status of the family. When categorical analysis was used, homes < 0.50 mile from a field had significantly higher bifenthrin house dust levels, and when using the CART modeling technique, the cut-off was further specified to be homes < 0.42 mile from a field. This finding was not consistent for permethrin, which could reflect the shorter soil half-life compared to bifenthrin, or also could be due to influence from residential pesticide applications.

***Elucidated a possible participant education gaps* -** Participants in one home reported that the farmworker removed his shoes upon arriving home from work as had been recommended, yet the participant's additionally said that in the morning the farmworker wore the shoes inside of the home while he was preparing to leave for the day. This suggests that certain families may not completely understand the significance behind recommendations they received such as not wearing shoes while inside the home. In fact, in this study, removing shoes right away upon arriving home was actually associated with higher levels of bifenthrin in the house dust. It is currently unclear whether this finding represents a widespread education gap warranting further investigation. Future studies would benefit from confirming that all study participants have a thorough understanding of the rationale behind removing shoes prior to entering the home.

***Reported effect of having carpeting in the home* -** In the current study, homes having carpet were found to be associated with increased levels of bifenthrin in house dust in both the univariate analysis and the Classification and Regression Tree (CART) modeling approach. This valuable finding adds to the already existent literature that asserts that mechanical cleaning processes, such as vacuuming, may not be effective at removing pesticides from a carpet or the foam pad underneath the carpet (Ferguson et al., 2008; Shin et al., 2013). It is possible that families may believe they are engaging in adequate cleaning habits, such as vacuuming, yet their efforts lack effectiveness. In this respect, researchers must be aware that although advising families to remove carpeting from their homes may be an effective intervention to reduce agriculture pesticides in house dust, the removal may actually be impractical, especially in low-income households. This information adds to the growing literature that suggests carpeted homes may lead to increased pesticide levels in the house dust and highlights the environmental justice issues related to being a lower socio-economic status farmworker family in an agricultural community.

Applications of Classification and Regression Tree (CART) Analysis

Used multivariate analysis technique - The current study used CART modeling, which is a less common technique in the fields of environmental health and public health. This is the first time, to the knowledge of the author of this dissertation, that CART modeling was used to identify influential household level risk factors for agricultural pesticides detection in residential outdoor air and yard soil and indoor house dust. By using the CART approach, the limitations of more traditional multi-variate statistical approaches, such as multiple linear or logistic regressions (Allison 1999; Agresti et al., 2007) were overcome. The CART results made a significant contribution by elucidating the best predictors of pesticide levels among many potentially influential factors while taking these multi-level comparisons into account. Agricultural applications were found to be the best predictors of detection in outdoor yard soil and air. A wider variety of predictors were identified for detection in indoor house dust, such as increased heating and cooling, a closer distance between home and agricultural field, and having at least one farmworker per 1,000 ft^2 of the home, along with greater agricultural applications in nearby fields.

Identified a possible threshold value at which agricultural applications may reduce effectiveness of household- level risk factors - For all of the CART models used in predicting house dust levels for bifenthrin, when agricultural applications were included among the many potentially influential household levels factors, the agricultural applications were identified as the only predictors. This was not the case for permethrin, however. These findings are a valuable contribution because they suggest that a certain threshold of pesticide application in the nearby field could reduce the effectiveness of household-level practices aimed at preventing agricultural pesticides from entering the home.

Distinguished between modifiable and non-modifiable household-level risk factors and soil track-in and air infiltration pathway factors - The results of the current study showed that all of the household-level predictors of bifenthrin in the house dust are not feasibly modifiable by the family, and are related to a combination of air infiltration and soil track-in pathways. On the other hand, for permethrin, the factors identified as predictors of detection frequency in house dust were modifiable factors related to the air infiltration pathway, but unfortunately, the CART approach was unable to build a model related to soil track-in pathway factors. The distinction between modifiable and non-modifiable factors, along with air infiltration and soil-track pathway factors, offers valuable insight into how effective household-level interventions can be at reducing agricultural pesticides in house dust, and provides an opportunity for researchers to hone in on modifiable factors related to either pathway, while still maintaining awareness of driving factors that are less feasibly modifiable.

***Quantified incremental excess cancer lifetime and non-cancer hazard quotient risks for aggregate and cumulative exposures* -** Results of this study showed that for bifenthrin and permethrin, the incremental excess lifetime cancer risk for aggregate and cumulative exposure via ingestion of soil and dust and inhalation of air were far below the one-in-one-million acceptable risk level, for all age groups. Likewise, for bifenthrin and permethrin, the hazard quotient for aggregate and cumulative exposure were much below one, which is considered the acceptable risk level for non-cancer risks. All exposure scenario assumptions were obtained from the 2011 Exposure Factors Handbook (USEPA, 2011a) or other standard default values determined by the USEPA (USEPA, 2015c). This study presented reasonable exposure scenarios for multiple age groups and quantified risk levels of each group.

8.2 Study Limitations and Lessons Learned

All research studies have some limitations for reasons such as funding constraints, lack of resources, shortcomings in research design or execution, questionable responses in self-reported data, or simply being outside of the scope of the research project. However, successful completion of a research study provides an opportunity for growth as a researcher because lessons are always learned. Some of the limitations and lessons learned from this dissertation study are as follows:

Field Sampling and Pesticide Analysis Limitations

Indoor air samples not obtained - Collection of additional samples was outside of the funding capabilities of this study and was initially considered unnecessary for effectively developing and evaluating the pesticide transport model using house dust as the outcome, which was the overall goal of this dissertation. However, indoor air samples could have contributed additional insight into potential indoor air pesticide exposures, particularly for trifluralin where there was a high detection frequency in outdoor air. In addition, permethrin would likely have been detected in the indoor air because it was estimated to partition 93% into the vapor phase. As a side note, indoor air samples would have been an inconvenience to the families as an active sampler was loud and required to run for forty-eight hours at each sampling date, accordingly, there may have been an increased chance of a family member refusing the sampling.

Statistical analyses limited by detection frequency of pesticides - Although the outdoor air, yard soil, and indoor house dust samples were analyzed for a suite of pesticides, just a few had a detection frequency high enough for further statistical analysis. Only bifenthrin and permethrin, along with trifluralin in a few instances, were used for further analysis to assess pathways of agricultural pesticides into farmworkers' homes and explore risk factors for increased household levels of agricultural pesticides.

Statistical analyses limited by study sample size - Only 21 farmworkers' homes were included in the study's testing, which was the maximum sample size possible based on the funding constraints. Due to this issue, it is possible that some of the risk factors that were not found to be statistically significant may have been significant if the sample size was larger. Additionally, a small sample size increases the risk that the results cannot be generalized. It is notable that the transport modeling was able to overcome the small sample size somewhat because a stochastic approach was used with 55,072 simulations. It is possible, however, that a larger sample size for the sampling phase would have yielded higher detection frequencies of pesticides, which would have allowed for the modeling of relative pathway contributions for more pesticides.

Possible underestimation of particles captured in outdoor air samples - The PUF/XAD-2/PUF cartridge, which was used to capture outdoor air samples, has been shown to be more efficient for capturing pesticides in the gas phase rather than the particle phase (Chuang et al., 1987; Odabasi et al. 1999; Wania et al., 2003). Also, the XAD-2 resin is known to retain small particles, which may not have been efficiently removed by solvent extraction, the technique used in this study (Grasshoff et al., 1999). Due to these reasons, it is possible that the level of particles may have been underestimated. A lesson learned from this is that it would have been useful to additionally place a glass fiber filter or quartz fiber filter in line with the PUF/XAD-2/PUF to more effectively capture particles.

Lack of information on pesticide applications in specific nearby fields - While there was generally a positive association between agricultural pesticide levels in the house dust and a closer distance from the home to nearest agricultural field, it cannot be said whether the pesticide of interest was applied in that nearest field. Given this lack of information, it was also not possible to effectively assess how wind direction may have affected pesticide transport away from fields and to homes.

Lack of differentiation between hard floor and carpet dust - In many of the homes, it was difficult to collect a house dust sample with enough mass to analyze for pesticides; accordingly, dust from hard floor and carpet were combined into a single sample. Therefore, although an association was found between having carpet in the house and concentration of bifenthrin in the house dust, it is not possible to conclude that bifenthrin levels in house dust were associated with typing of flooring of the dust sample. Also, the failure to differentiate between hard floor and carpet made it impossible to capture the “non-mobile” phase (i.e., dust from carpet and underlying foam pad) versus the “mobile” phase (i.e., dust from hard floor). This may be problematic because a previous study found that when the “non-mobile” and “mobile” phases were considered separately, the residence time of pesticides was on the order of years (Shin et al., 2013), which is much higher than the residence times computed in the current study. Therefore, the residence times from this study should be considered with caution. A lesson learned from this is that samples from hard floors and carpet should be collected separately so that contributions from each floor type can be quantified; these samples can be later combined for analysis if necessary.

Questionable Responses in Self-Reported Data - Questionnaire data is limited by the responses of the participant, which could contain errors due to cultural biases, memory lapses, or feeling pressure to answering questions in a certain way. For example, the discrepancy between the participant-reported distances between home and nearest agricultural field illustrates where the questionnaire data may not have been accurate. A lesson learned from this limitation is that response triangulation should be performed, which is a method that asks the participant the same question in different ways to help confirm that the questionnaire response is accurate. Another lesson learned is that it may be useful to inform the participants ahead of time that it will be necessary to attain information. In the current study, some families did not know which residential pesticides they used, while others did not know which pesticides were applied professionally. In some cases, the participant interviewed was the wife instead of the farmworker who was at work at the time of the interview. It is possible that the farmworker spouse may have had more information about pesticides used residentially, and if the family knew ahead of time that they had to gather this information.

Classification and Regression Tree (CART) Modeling Limitations

***Compromised stopping rule* -** The minimum splitting requirement was set to having an available sample size of five for both resultant node, and thus the "stopping rule" was set to a sample size less than five in each node. The more common lower limit for the "stopping rule" is a sample size less than 10, but in this study, the limit was lowered based on the overall small sample size of only 21 homes. In some cases of permethrin, it was not possible to grow a tree due to the inability to meet the minimum split requirement, which caused the model to apply the "stopping rule."

***Trade-off between numbers of identified factors and CART accuracy* -** In this study, a model with high prediction accuracy and also a decent number of identified predictors could not be achieved. For bifenthrin, more predictors were identified, yet prediction accuracy was moderate at best. Conversely, factors were identified for permethrin, yet prediction accuracy was moderate-to-high.

Optimal Complexity Parameter (CP) could not always be used - The optimal CP value, which effectively minimizes the misclassification error in CART modeling, was not use whenever it caused the tree to have no splits. For those CART models, the lowest CP value that still allowed for at least one split was alternatively used, and effectively pruning of the tree was inevitably compromised.

Risk Assessment Limitations

Risk assessment captured only one percent of pesticides applied - According to the Arizona Department of Agriculture (AZDA, 2014), 157 different types of pesticides were applied over the sampling period of this study. However, only two of the pesticides could be used for the aggregate and cumulative risk assessments, meaning that only one percent of the pesticides applied were captured in these risk assessments. Although bifenthrin and permethrin were within the acceptable risk levels, agricultural pesticide exposure could still be a concern.

Risk assessment has uncertainties and assumptions - Risk assessments are limited by uncertainties in the data used and often rely on a set of assumptions. For the dose-response assessment, uncertainties were taken into account by using uncertainty/safety factors provided by the Food Quality Protection Act (FQPA) (NAS 1993), but they are only a rough estimate because these factors are either applied at a set level or removed all together. In addition, potential exposure scenarios include assumptions, based mostly on national averages, which may not have been representative of the study population of interest.

8.3 Future Directions

Prior studies attempting to reduce agricultural pesticides in farmworker homes were generally based on solely the take-home/soil track-in pathway. These studies had limited success. The current study has shown the high significance of the air infiltration pathway in contributing to the agriculture pesticide transport into the homes nearby agricultural fields. Future interventions should consider shifting their focus to more aggressively target the air infiltration pathway in conjunction with the take-home/soil track-in pathway.

The high significance of the air infiltration pathway in the current study implies that there is wide-ranging concern with respect to increased agricultural pesticide levels in house dust, regardless of whether the home or community resident works in the agricultural fields. Therefore, it would be wise to consider not only the farmworkers' behaviors on contributions to pesticide levels in household dust, but to expand consideration to the behavior contributions of the entire family. Also, a valuable future study could be the application of the current modeling framework to datasets that include both farmworker and non-farmworker homes in an agricultural community. No such dataset exists at this time, and new sampling initiatives would greatly enhance the understanding the how farmworker status in the home affects contributions of agricultural pesticide pathways into the house dust.

The results of the current study suggest that there are multiple modifiable factors to the air infiltration pathway (e.g., the homes cooling and heating, windows and doors, air filters) that can affect agricultural pesticide levels in the homes. Optimization of these modifiable factors should be pursued in future studies. For example, it is likely that the optimal frequency for opening windows and doors is rooted in the effect of ventilation in the home, but this optimal frequency remains undetermined. It is recommended that future studies explore creative possibilities to increase the air exchange rate without compromising temperature control in the home. Also, increased changing of air filters was associated with higher pesticide levels in the house dust, and thus, future experiments could be designed to find the optimal changing frequency that maximizes the “filter cake effect,” while still maintaining its effectiveness as an air filter. There may also be variations in the effectiveness of different types of air filters, an effect that could not be captured in this study. Future studies should be designed to test the effectiveness of a variety of air filters on the reduction of air infiltration of pesticides into the home.

It is recommended that future questionnaires ask more specific questions about modifiable factors at the household level, particularly those related to the air infiltration pathway. For example, it would be useful to ask families to specify the type of air filters used. Also, since many families reported changing air filters at a high frequency, it would also be helpful to know why they choose to do so. Finally, for those that clean their air filters, it would be relevant to ask what kind of method they use (e.g., wash it; hit it against a firm surface). There is a great opportunity for future questionnaires to build upon the current study’s questionnaire in order to more effectively assess risk factors for agricultural pesticides at the home environment.

The findings of this study have also highlighted the great need to begin shifting the burden away from farmworkers and their families and onto agricultural growers in order to prevent pesticides from being transported away from fields. While the results of the current study pinpoint several factors at the household level that may be further explored to help prevent agricultural pesticides from entering homes, the findings also suggest that living in the presence of high agricultural applications may cause efforts at the household level to be partially or completely ineffective. In fact, it is possible that many families may have a false sense of security because they do engage in practices that they believe help prevent pesticides from entering their homes, yet these practices lack effectiveness. It is without a doubt that major policy initiatives are needed to truly prevent agricultural pesticides from being transported away from fields and into homes.

Appdendix A

Code For Pesticide Model Evaluation

```
#Monte Carlo Simulations
#n=55,072

library(nortest)
library(truncnorm)
library(EnvStats)
library(fitdistrplus)

#DISTRIBUTIONS
par(mfrow = c(2, 1))

#Floor Area
afl<-c(141.68,129.32, 100.34, 61.69, 85.56, 89.93,
82.50,209.40,66.33,139.35,51.27,78.42,191.75, 108.53, 344.67, 107.02, 96.62, 62.80,
79.66, 235.79, 113.81)
fitnafl<-fitdist(afl, "norm")
summary(fitnafl)
fitwafl <- fitdist(afl, "weibull")
summary(fitwafl)
#not weibull
fitgafl<- fitdist(afl, "gamma")
summary(fitgafl)
#not gamma
fitlnafl <- fitdist(afl, "lnorm")
summary(fitlnafl)
fiteafl<-fitdist(afl, "exp")
summary(fiteafl)
denscomp(list(fitnafl, fitwafl,fitgafl,fitlnafl,
fiteafl),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),fitcol=c("red", "blue","purple", "black", "green"),main="Floor Area
fits",xlab="area (m2)",ylab="F",xlim = c(0,350),xlegend = "right")
cdfcomp(list(fitnafl, fitwafl,fitgafl,fitlnafl,
fiteafl),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),fitcol=c("red", "blue","purple", "black", "green"),main="Floor Area
fits",xlab="area (m2)",ylab="F",xlim = c(0,350),xlegend = "right")
#testing lognormal dis
ks.test(afl, "plnorm", mean(log(afl)), sd(log(afl)))
#using lognormal, truncate
afl.lnorm.trunc<-rlnormTrunc(55072, mean=mean(log(afl)), sd = sd(log(afl)), min =
min(afl)-(min(afl)*0.05), max = max(afl)+(max(afl)*0.05))

#Volume of House
```

```
V=afl.lnorm.trunc * h.norm.trunc

##Mass Loading on Floor- lognormal distribution
mfl<-
c(21.8079320,1.3483323,7.0925797,0.4215011,0.3529472,2.2239343,0.3108296,1.1
381182,50.0972684,5.3380590,1.3689881,16.2455385,2.4673529,6.7739403,3.20708
30,0.1531788,2.3975451,1.9577789)
fitnmfl<-fitdist(mfl, "norm")
summary(fitnmfl)
fitwmfl <- fitdist(mfl, "weibull")
summary(fitwmfl)
fitgmfl<- fitdist(mfl, "gamma")
summary(fitgmfl)
fitlnmfl <- fitdist(mfl, "lnorm")
summary(fitlnmfl)
fitemfl<-fitdist(mfl, "exp")
summary(fitemfl)
denscomp(list(fitnmfl, fitwmfl,fitgmfl,fitlnmfl,
fitemfl),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Mass Loading on Floors fits",xlab="loading
(g/m2)",ylab="F",xlim = c(0,60),ylim=c(0,0.2), xlegend = "right")
cdfcomp(list(fitnmfl, fitwmfl,fitgmfl,fitlnmfl,
fitemfl),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Mass Loading on Floors fits",xlab="loading
(g/m2)",ylab="F",xlim = c(0,25), ylim=c(0,1), xlegend = "right")
#testing lognormal dis
mlmfl=mean(log(mfl))
sdmfl=sd(log(mfl))
mfl.lnorm<-rlnorm(55072, mean(log(mfl)), sd(log(mfl)))
ks.test(mfl, "plnorm", mlmfl, sdmfl)
#using lognormal, truncate
mfl.lnorm.trunc<-rlnormTrunc(55072, meanlog = mlmfl, sdlog = sdmfl, min =
min(mfl)-(min(mfl)*0.05), max = max(mfl)+(max(mfl)*0.05))

#Concentration of Organic Matter in Soil
coms<-
c(0.03428571,0.04500000,0.03246753,0.07679325,0.03793627,0.03111111,0.03756
201,0.06364749,0.06228374,0.03306728,0.04340659,0.06618611,0.02233251,0.0735
2941,0.05702648,0.04953146,0.04430380,0.03385417,0.06839623,0.04210526,0.075
84830)
fitncoms<-fitdist(coms, "norm")
summary(fitncoms)
fitwcoms <- fitdist(coms, "weibull")
summary(fitwcoms)
#not weibull
fitgcoms<- fitdist(coms, "gamma")
```

```
summary(fitgcoms)
#not gamma
fitlncoms <- fitdist(coms, "lnorm")
summary(fitlncoms)
fitecoms<-fitdist(coms, "exp")
summary(fitecoms)
denscomp(list(fitncoms, fitwcoms,fitgcoms,fitlncoms,
fitecoms),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Concentrations of OM in Soil fits",xlab="concentration
(g/g)",ylab="F",xlim = c(0,0.1),ylim=c(0,40), xlegend = "bottomright")
cdfcomp(list(fitncoms, fitwcoms,fitgcoms,fitlncoms,
fitecoms),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Concentrations of OM in Soil fits",xlab="concentration
(g/g)",ylab="F",xlim = c(0,0.1), ylim=c(0,1), xlegend = "right")
#testing lognormal dis
mlcoms=mean(log(coms))
sdlcoms=sd(log(coms))
ks.test(coms, "plnorm", mean(log(coms)), sd(log(coms)))
#using lognormal, truncate
coms.lnorm.trunc<-rlnormTrunc(55072, meanlog = mlcoms, sdlog = sdlcoms, min =
min(coms)-(min(coms)*0.05), max = max(coms)+(max(coms)*0.05))


#Ceiling Heights
h<-
c(2.441,2.741,2.440,2.442,2.443,2.740,2.445,3.050,3.051,3.052,2.446,2.447,2.29,2.4
48,2.742,2.449,2.4411,2.4412,2.743,2.4413,2.13)
hist(h)
plot(ecdf(h))
min(h)
mean(h)
max(h)
hist(h)
fitnh<-fitdist(h, "norm")
summary(fitnh)
fitwh <- fitdist(h, "weibull")
summary(fitwh)
fitgh <- fitdist(h, "gamma")
summary(fitgh)
fitlnh <- fitdist(h, "lnorm")
summary(fitlnh)
fiteh<-fitdist(h, "exp")
summary(fiteh)
par(mfrow = c(2, 1))
denscomp(list(fitnh, fitwh,fitgh,fitlnh,
fiteh),legendtext=c("normal","weibull","gamma","lognormal",
```

```
"exponential"),main="Ceiling Height fits",xlab="height (m)",ylab="F",xlim =
c(2,4),xlegend = "right")
cdfcomp(list(fitnh, fitwh,fitgh,fitlnh,
fiteh),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Ceiling Height fits",xlab="height (m)",ylab="F",xlim =
c(2,4),xlegend = "right")
gofstat(list(fitnh, fitwh,fitgh,fitlnh, fiteh),fitnames =
c("normal","weibull","gamma","lognormal", "exponential"))
#problem with gofstat, although visually from plots it looks like normal or lognormal
fits
#testing normal dis
ks.test(h, "pnorm", mean(h), sd(h))
ks.test(h, "plnorm", mean(log(h)), sd(log(h)))
#problem with lognormal bc ties, use normal
#using lognormal, truncate
library(truncnorm)
a=(min(h))-(min(h)*0.05)
b=(max(h))+(max(h)*0.05)
h.norm.trunc<-rtruncnorm(55072, a,b, mean=mean(h), sd=sd(h))

#Dust Fall Rates
df<- c(0.010,0.0051,0.004,0.021,0.009,0.0052,0.0053,0.0071,0.0072)
fitndf<-fitdist(df, "norm")
summary(fitndf)
fitwdf<-fitdist(df,"weibull")
summary(fitwdf)
#won't fit weibull
summary(fitwdf)
fitgdf<- fitdist(df, "gamma")
summary(fitgdf)
#won't fit gamma
summary(fitgdf)
fitlndf <- fitdist(df, "lnorm")
summary(fitlndf)
fitedf<-fitdist(df, "exp")
summary(fitedf)
denscomp(list(fitndf, fitwdf,fitgdf,fitlndf,
fitedf),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Rate of Dust Fall onto Floors fits",xlab="loading
(g/m2/d)",ylab="F",xlim = c(0,0.025),ylim=c(0,150), xlegend = "right")
cdfcomp(list(fitndf, fitwdf,fitgdf,fitlndf,
fitedf),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Rate of Dust Fall onto Floors fits",xlab="loading
(g/m2/d)",ylab="F",xlim = c(0,0.025), ylim=c(0,1), xlegend = "right")
#testing lognormal dis
mldf=mean(log(df))
```

```
sdldf=sd(log(df))
ks.test(df, "plnorm", mldf, sdldf)
#issue with ties so added integer at end
#using lognormal, truncate
df.lnorm.trunc<-rlnormTrunc(55072, mldf, sdldf, min = min(df)-(min(df)*0.05), max
= max(df)+(max(df)*0.05))

#Outdoor Total Suspended Particles
tspo<- c(7.69e-5,2.41e-6,2.06e-5,1.35e-4,2.96e-5,2.08e-5,5.53e-5,2.49e-5,7.39e-6)
fitntspo<-fitdist(tspo, "norm")
summary(fitntspo)
#not normal
fitwtspo <- fitdist(tspo, "weibull")
summary(fitwtspo)
#not weibull
fitlntspo <- fitdist(tspo, "lnorm")
summary(fitlntspo)
fitetspo<-fitdist(tspo, "exp")
summary(fitetspo)
fitgtspo<-fitdist(tspo, "gamma")
summary(fitgtspo)
denscomp (list(fitlntspo, fitetspo, fitgtspo),legendtext=c("lognormal", "exponential",
"gamma"), main="TSPo fits",xlab= "TSPo (g/m3)",ylab="F", xlegend = "right")
cdfcomp(list(fitlntspo, fitetspo, fitgtspo),legendtext=c("lognormal", "exponential",
"gamma"),main="TSPo fits", xlegend = "right")
#testing lognormal dis
ks.test(tspo, "plnorm", mean(log(tspo)), sd(log(tspo)))
#using lognormal, truncate
tspo.lnorm.trunc<-rlnormTrunc(55072, mean(log(tspo)), sd(log(tspo)), min =
min(tspo)-(min(tspo)*0.05), max = max(tspo)+(max(tspo)*0.05))

#Concentration of Bifenthrin in Soil
cps_bif<-c(0.014142136,0.014142136,0.014142136,0.014142136,
0.014142136,0.014142136,0.014142136,0.014142136,0.013966589,0.014142136,0.0
14142136,0.014142136, 0.132910906, 0.014142136,0.042440837, 0.014142136,
0.023738424,0.039203765,0.122043739,0.042423054,0.012969021)
fitncpsbif<-fitdist(cps_bif,"norm")
summary(fitncpsbif)
fitwcpsbif <- fitdist(cps_bif, "weibull")
summary(fitwcpsbif)
#not weibull
fitgcpsbif<- fitdist(cps_bif, "gamma")
summary(fitgcpsbif)
#not gamma
fitlncpsbif <- fitdist(cps_bif, "lnorm")
summary(fitlncpsbif)
```

```
fitecpsbif<-fitdist(cps_bif, "exp")
summary(fitecpsbif)
denscomp(list(fitncpsbif, fitwcpsbif,fitgcpsbif,fitlncpsbif,
fitecpsbif),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Bifenthrin in Soil fits",xlab="conc (microgr/g)",ylab="F",xlim
= c(0,0.2),xlegend = "right")
cdfcomp(list(fitncpsbif, fitwcpsbif,fitgcpsbif,fitlncpsbif,
fitecpsbif),legendtext=c("normal","weibull","gamma","lognormal",
"exponential"),main="Bifenthrin in Soil fits",xlab="conc (microgr/g)",ylab="F",xlim
= c(0,0.2),xlegend = "right")
#testing lognormal dis
ks.test(cps_bif, "plnorm", mean(log(cps_bif)), sd(log(cps_bif)))
ml
#using lognormal, truncate 38%D and 62%ND
cps_bif.lnorm.trunc<-rlnormTrunc(20928,mean(log(cps_bif)), sd(log(cps_bif)), min
= 0.02, max = (max(cps_bif)+ max(cps_bif)*0.05))
cps_bif.cens.lnorm.trunc<-rlnormTrunc(34144, mean(log(cps_bif)), sd(log(cps_bif)),
min = 0, max=0.02)
cps_bif_combo=c(cps_bif.lnorm.trunc, cps_bif.cens.lnorm.trunc)


#Concentration of Bifenthrin in Outdoor Air on Particles, 43%D and 57%ND
oapartbif<-
c(0.000570841,0.000570841,0.000125694,0.000570841,0.000094200,0.000570841,0
.000570841,0.000570841,0.000570841,0.000570841,0.000632463,0.003569248,0.00
0190757,
0.000570841,0.000570841,0.000570841,0.002304704,0.000570841,0.000680661,0.0
01151000)
fitnoapartbif<-fitdist(oapartbif, "norm")
summary(fitnoapartbif)
#not normal
fitwoapartbif <- fitdist(oapartbif, "weibull")
summary(fitwoapartbif)
#not weibull
fitgoapartbif <- fitdist(oapartbif, "gamma")
summary(fitgoapartbif)
#not gamma
fitlnoapartbif<- fitdist(oapartbif, "lnorm")
summary(fitlnoapart)
fiteoapartbif<-fitdist(oapartbif, "exp")
summary(fiteoapartbif)
denscomp(list(fitlnoapartbif, fiteoapartbif), legendtext=c("lognormal", "exponential"),
main="Bifenthrin in Outdoor Air on Particles fits",xlab="conc (ug/g)",ylab="F",xlim
= c(0,0.004),ylim=c(0,1200),xlegend = "right")
```

```
cdfcomp(list(fitlnoapartbif, fiteoapartbif), legendtext=c("lognormal", "exponential"),
main="Bifenthrin in Outdoor Air on Particles fits",xlab="conc (ug/g)",ylab="F",xlim
= c(0,0.004),ylim=c(0,1.2),xlegend = "right")
oa_particle_bif.lnorm<-rlnorm(55072,mean(log(oa_particle_bif)),
sd(log(oa_particle_bif)))
mloapartbif=mean(log(oa_particle_bif))
sdloapartbif=sd(log(oa_particle_bif))
#testing lognormal dis
ks.test(oa_particle_bif, "plnorm", mloapartbif, sdloapartbif)
#using lognormal, truncate
oa_particle_bif.lnorm.trunc<-rlnormTrunc(23680,mean(log(oa_particle_bif)),
sd(log(oa_particle_bif)), min = 0.000868, max =
max(oa_particle_bif)+(max(oa_particle_bif)*0.05))
oa_particle_bif.lnorm.trunc<-rlnormTrunc(31391,mean(log(oa_particle_bif)),
                                        sd(log(oa_particle_bif)), min = 0, max = 0.000868)
oapartbif_combo=c(oa_particle_bif.lnorm.trunc,oa_particle_bif.lnorm.trunc)


#Concentration of Bifenthrin in Outdoor Total Suspended Particles
CSTSPo_bif=oapartbif_combo/tspo.lnorm.trunc

#ACH-based on Pandian et al. 1998
#creating an array of percentiles
p<-c(0.05,0.25,0.50,0.75,0.95)
#creating an arary of corresponding values
ach<-c(0.585, 3.84,8.4,14.88,22.8,47.28)
hist(ach)
meanlog_ach<-(log(3.84)+ log(47.28))/2
meanlog_ach
mean_ach<-(3.84)+(47.28)/2
mean_ach
sd_ach<-(3.84-mean_ach)/qnorm(0.05)
sd_ach
sdlog_ach <- (log(3.84) - meanlog_ach) / qnorm(0.05)
sdlog_ach

fitnach<-fitdist(ach, "norm")
summary(fitnach)
fitwach <- fitdist(ach, "weibull")
summary(fitwach)
fitgach <- fitdist(ach, "gamma")
summary(fitgach)
fitlnach <- fitdist(ach, "lnorm")
summary(fitlnach)
fiteach<-fitdist(ach, "exp")
summary(fiteach)
```

```
denscomp(list(fitnach, fitwach, fitgach, fitlnach, fiteach), legendtext=c("normal",
"weibull", "gamma", "lognormal", "exponential"), main="Air Exchange
Rates",xlab="rate (1/d)",ylab="F", xlegend = "right")
cdfcomp(list(fitnach, fitwach, fitgach, fitlnach, fiteach),
legendtext=c("normal","weibull", "gamma", "lognormal", "exponential"), main="Air
Exchange Rates",xlab="rate (1/d)",xlegend = "right")
#testing lognormal dis
ks.test(ach, "plnorm", meanlog_ach, sdlog_ach)
#use lognormal, truncate
ach.lnorm.trunc<-rlnormTrunc(55072, meanlog_ach, sdlog_ach, min = min(ach)-
(min(ach)*0.05), max = max(ach)+(max(ach)*0.05))


#vbarr
vbarr.unif<-runif(55072,135, 234)
#vbaro
vbaro.unif<-runif(55072,14,26)
#kd
kd_bif.unif<-runif(55072,0.006,0.0107)
#p
p_unif<-runif(55072, 0.9,1)

#Fixed Values
R<-0.011
Ts<-0.099
P<-0.96
Fom<-0.074
Csom<-0
Cln2<-0.0053
#Compute pesticide in in floor dust
Cpfl_meas_bif<-c(2.24170981, 0.014142136, 0.155143871,
0.014142136,0.014142136,
0.213781602,0.033425451,0.065595875,0.186799469,0.014142136,
        0.014142136,0.014142136, 0.39798218,
0.014142136,0.368500974,0.014142136, 1.01589404,
0.014142136,0.293532942,0.014142136,0.014142136)

exp(mean(log(Cpfl_meas_bif)))
#gm of cpfl_meas=  0.05641995
mean(Cpfl_meas_bif)
sd(Cpfl_meas_bif, na.rm = FALSE)

Cpfl_num_bif_55072<-(ach.lnorm.trunc* Csom* Fom * V) + (Csom * Fom*
kd_bif.unif * V) +
 (ach.lnorm.trunc* cps_bif_combo* Ts* V) + (cps_bif_combo* kd_bif.unif * Ts* V)
+
```

```
 (ach.lnorm.trunc* afl.lnorm.trunc * CSTSPo_bif * p_unif * tspo.lnorm.trunc* V *
vbaro.unif) +
 (afl.lnorm.trunc * Csom * Fom* vbarr.unif) + (afl.lnorm.trunc *cps_bif_combo * Ts
* vbarr.unif)

Cpfl_denom_bif_55072<-(afl.lnorm.trunc * mfl.lnorm.trunc * ((ach.lnorm.trunc *
Cln2 * V) + (ach.lnorm.trunc* kd_bif.unif * V) + (Cln2* kd_bif.unif * V) +
((kd_bif.unif*kd_bif.unif) * V) + (ach.lnorm.trunc * R * V) + (kd_bif.unif * R * V) +
(afl.lnorm.trunc * Cln2 * vbarr.unif) + (afl.lnorm.trunc * kd_bif.unif * vbarr.unif)))


Cpfl_est_final_bif_55072 = Cpfl_num_bif_55072/Cpfl_denom_bif_55072
mean(Csfl_est_final_bif_55072)
min(Csfl_est_final_bif_55072)
max(Csfl_est_final_bif_55072)
quantile(Csfl_est_final_bif_55072, c(0, .25, .5, .75, 1))


#Statistical Tests
ln_Csfl_est_final_bif_55072=log(Csfl_est_final_bif_55072)
ln_Csfl_meas_bif=log(Csfl_meas_bif)
mean(ln_Csfl_est_final_bif_55072)
t.test(ln_Csfl_meas_bif, alternative="two.sided", mu=  -3.161821)


#Graphics
parmfrow=c(1,1)
ln_Csfl_est_final_bif_55072=log(Csfl_est_final_bif_55072)
ln_Csfl_meas=log(Csfl_meas_bif)
boxplot(ln_Csfl_est_final_bif_55072,ln_Csfl_meas_bif,cex=2,
names=c("Estimated","Measured"),
col=c("blue","yellow"),
xlab="ln(concentration) (micrg/g)",
main="Bifenthrin in Floor Dust")
```

Appendix B

Code for Model Application to Estimate Realtive Contributions of Air Infiltration and Soil Track-in to House Dust and Residence Time in House Dust for Bifenthrin and Permethrin

```
#Using Model to Estimate Relative Contribution of Pathways and Residence Time
library(truncnorm)
library(nortest)


#Bifenthrin Relative Contributions
#In-track
Intrack_bif=cps_bif_combo*Ts
min(Intrack_bif)
mean(Intrack_bif)
max(Intrack_bif)

#In-air
Inair_bif=((ach.lnorm.trunc*p_unif*h.norm.trunc*oapartbif_combo)/(vbaro.unif*ach.lnorm.trunc*h.norm.trunc))*(vbaro.unif*afl.lnorm.trunc)
min(Inair_bif)
mean(Inair_bif)
max(Inair_bif)

#In-track percent
Intrack_percen_bif= (Intrack_bif/(Intrack_bif+ Inair_bif))* 100
min(Intrack_percen_bif)
mean(Intrack_percen_bif)
max(Intrack_percen_bif)
quantile(Intrack_percen_bif,c(.05,.25,.5, .75, .95))


#In-air percent
Inair_percen_bif= (Inair_bif/(Intrack_bif+Inair_bif))*100
min(Inair_percen_bif)
mean(Inair_percen_bif)
max(Inair_percen_bif)
quantile(Inair_percen_bif, c(.05,.25,.5, .75, .95))

#Residence time
out.exf_bif= ((mfl.lnorm.trunc * Csfl_est_final_bif_55072 * R)/(vbarr.unif+ach.lnorm.trunc*h.norm.trunc))*(ach.lnorm.trunc*h.norm.trunc*afl.lnorm.trunc)
out.cln_bif= (Cln2*afl.lnorm.trunc*mfl.lnorm.trunc*Csfl_est_final_bif_55072)
```

```
out.decay_bif=
(kd_bif.unif*afl.lnorm.trunc*mfl.lnorm.trunc*Csfl_est_final_bif_55072)
T_bif=((oapartbif_combo*afl.lnorm.trunc*h.norm.trunc)+(Intrack_bif*mfl.lnorm.tru
nc*afl.lnorm.trunc))/ (out.exf_bif + out.cln_bif + out.decay_bif)
min(T_bif)
median(T_bif)
max(T_bif)
quantile(T_bif, c(.05,.25,.5, .75, .95))
```

#Permethrin Relative Contributions

```
 #Permethrin Concentrations
#Cps_perm- lognormal, 90%D,10%ND
cps_perm<-
c(0.005656854,0.103649205,0.005656854,0.340520446,0.043463035,0.005656854,0
.053051512,0.387764449,0.04500777,0.041004265,0.020810464,0.311212181,0.029
844556,0.42980517,0.087580677,0.21061008,0.045360045,0.1637576,0.63967486,0.
119055087,0.116066962)
cps_perm.lnorm<-rlnorm(55072, mean(log(css_perm)), sd(log(css_perm)))
ks.test(cps_perm, "plnorm", mean(log(css_perm)), sd(log(css_perm)))
#using lognormal
mlcps_perm=mean(log(cps_perm))
sdcps_perm=sd(log(cps_perm))
cps_perm.lnorm.trunc<-rlnormTrunc(55072,meanlog=mlcss_perm,
sdlog=sdcss_perm, min = 0.004, max = max(cps_perm)+(max(cps_perm)*0.05))
cps_perm.cens.lnorm.trunc<-rlnormTrunc(55072,meanlog=mlcss_perm,
sdlog=sdcss_perm, min = 0, max=0.004)
cps_perm_combo=c(cps_perm.lnorm.trunc, cps_perm.cens.lnorm.trunc)

#oaparticle_perm- lognormal, 19%D, 81%ND
oapartperm<-c(1.964191E-05,1.964192E-05,1.964193E-05,1.964194E-
05,1.964195E-05,0.00002048,1.964196E-05,1.964197E-05,1.964198E-
05,1.964199E-05,0.000191044,5.55653E-05,1.9641911E-05,1.9641912E-
05,1.9641913E-05,4.67581E-05,1.9641914E-05,1.9641915E-05,1.9641916E-
05,1.9641917E-05,1.9641918E-05)
oapartpermd.lnorm.trunc<-rlnormTrunc(149,mean(log(oapartperm)),
sd(log(oapartperm)), min = 0.000174, max =
max(oapartperm)+(max(oapartperm)*0.05))
oapartpermnd.lnorm.trunc<-rlnormTrunc(634,mean(log(oapartperm)),
sd(log(oapartperm)), min = 0, max =0.000174)
oapartperm_combo=c(oapartpermd.lnorm.trunc, oapartpermnd.lnorm.trunc)
ks.test(oapartperm_combo, "plnorm", mean(log(oapartperm_combo)),
sd(log(oapartperm_combo)))
#using lognormal

#Concentration of Bifenthrin in Outdoor Total Suspended Particles
```

```
CSTSPo_perm=oapartperm_combo/tspo.lnorm.trunc

#kd
kd_perm.unif<-runif(55072,0.006,0.0598)

Cpfl_num_perm_55072<-(ach.lnorm.trunc* Csom* Fom * V) + (Csom * Fom*
kd_perm.unif * V) + (ach.lnorm.trunc* cps_perm_combo* Ts* V) +
(cps_perm_combo* kd_perm.unif * Ts* V) + (ach.lnorm.trunc* afl.lnorm.trunc *
CSTSPo_perm * p_unif * tspo.lnorm.trunc* V * vbaro.unif) + (afl.lnorm.trunc *
Csom * Fom* vbarr.unif) + (afl.lnorm.trunc *cps_perm_combo * Ts * vbarr.unif)


Cpfl_denom_perm_55072<-(afl.lnorm.trunc * mfl.lnorm.trunc * ((ach.lnorm.trunc *
Cln2 * V) +  (ach.lnorm.trunc* kd_perm.unif * V) + (Cln2* kd_perm.unif * V) +
((kd_perm.unif*kd_perm.unif) * V) + (ach.lnorm.trunc * R * V) +
(kd_perm.unif * R * V) + (afl.lnorm.trunc * Cln2 * vbarr.unif) +   (afl.lnorm.trunc *
kd_perm.unif * vbarr.unif)))

Cpfl_est_final_perm_55072 = Cpfl_num_perm_55072/Cpfl_denom_perm_55072


#Permethrin Relative Contributions
#In-track
Intrack_perm=cps_perm_combo*Ts
min(Intrack_perm)
mean(Intrack_perm)
max(Intrack_perm)

#In-air
Inair_perm=((ach.lnorm.trunc*p_unif*h.norm.trunc*oapartperm_combo)/(vbaro.unif
*ach.lnorm.trunc*h.norm.trunc))*(vbaro.unif*afl.lnorm.trunc)
min(Inair_perm)
mean(Inair_perm)
max(Inair_perm)

#In-track percent
Intrack_percen_perm=(Intrack_perm/(Intrack_perm+ Inair_perm))* 100
min(Intrack_percen_perm)
mean(Intrack_percen_perm)
max(Intrack_percen_perm)
quantile(Intrack_percen_perm, c(.05,.25,.5, .75, .95))

#In-air percent
Inair_percen_perm=(Inair_perm/(Intrack_perm+Inair_perm))*100
min(Inair_percen_perm)
mean(Inair_percen_perm)
```

```
max(Inair_percen_perm)
quantile(Inair_percen_perm, c(.05,.25,.5, .75, .95))


#Residence Time
out.exf_perm= (ach.lnorm.trunc*h.norm.trunc*afl.lnorm.trunc)*((mfl.lnorm.trunc *
Csfl_est_final_perm * R)/(vbarr.unif+ach.lnorm.trunc*h.norm.trunc))
out.cln_perm= (Cln2*afl.lnorm.trunc*mfl.lnorm.trunc*Csfl_est_final_perm)
out.decay_perm=
(kd_perm.unif*afl.lnorm.trunc*mfl.lnorm.trunc*Csfl_est_final_perm)
T_perm=((oapartperm_combo*afl.lnorm.trunc*h.norm.trunc)+(Csfl_est_final_perm*
mfl.lnorm.trunc*afl.lnorm.trunc))/
 (out.exh_perm + out.cln_perm + out.decay_perm)
min(T_perm)
mean(T_perm)
max(T_perm)
quantile(T_perm, c(.05,.1, .25,.5, .75, .9, .95, .96, .97, .98, .99))


par(mfrow = c(1, 1))
boxplot(Inair_percen_bif, Intrack_percen_bif, names=c("% Air Infiltration", "% Soil
Track-in"), col=c("red", "blue"), xlab="Bifenthrin in House Dust (ng/g)", main=
"Pathway Contributions of Bifenthrin in House Dust")
boxplot(Inair_percen_perm, Intrack_percen_perm, names=c("% Air Infiltration", "%
Soil Track-in"), col=c("red", "blue"), xlab="Permethrin in House Dust (ng/g)", main=
"Pathway Contributions of Permethrin in House Dust")
```

Appendix C

Best-Fit Distributions for Input Variables to Estimate C_{fl}^{p}

The best–fit distributions of each input variable to estimate C_{fl}^{p} determined through visual and statistical methods. Visually, potential distributions were overlaid on a histogram and cumulative distribution plot (CDF) for each input variable. Based on the suspected best-fit distribution from the visual plots, a Kolmorgorov-Smirnov (K-S) Goodness of Fit test was applied in which the null hypothesis was that the data follow the suspected distribution. A p-value of greater than 0.05 fails to reject the null hypothesis that the data follow the suspected distribution, and was therefore determined to be the best-fit distribution. Visual plots can be seen in Figures C-1 – Figure C-8. Results of the K-S tests and final best-fit distributions can be seen in Table C-1.

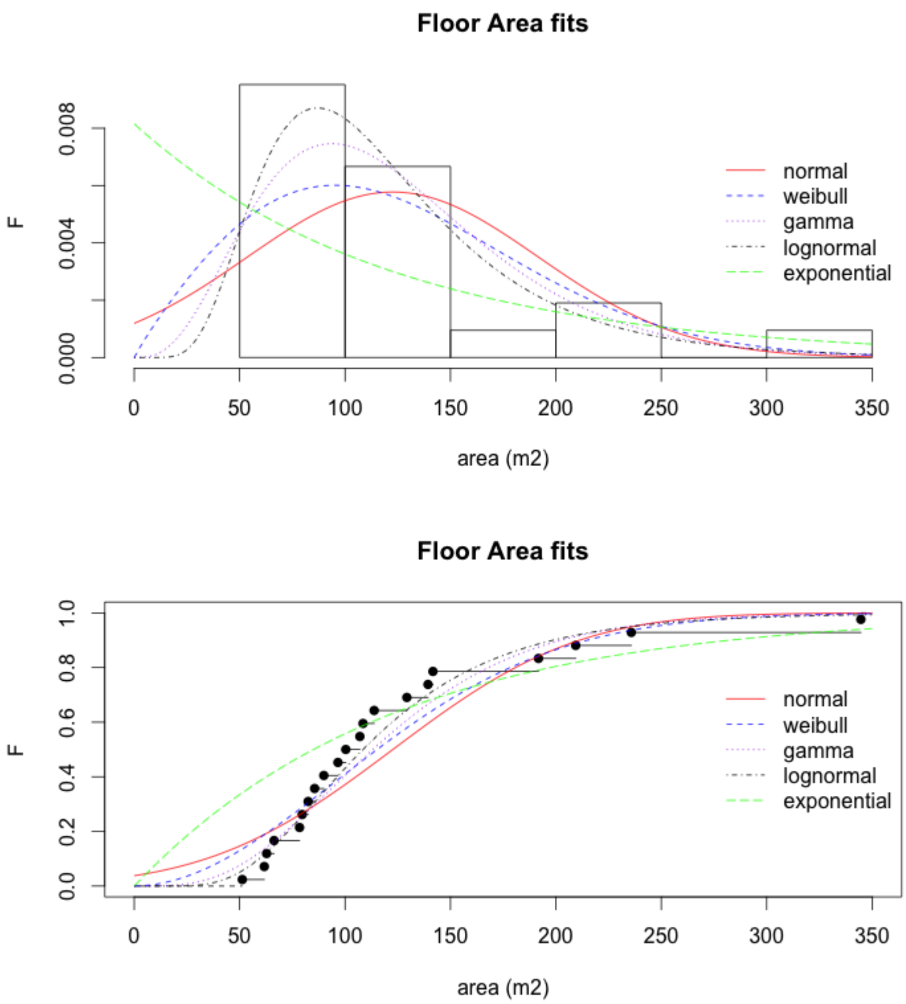
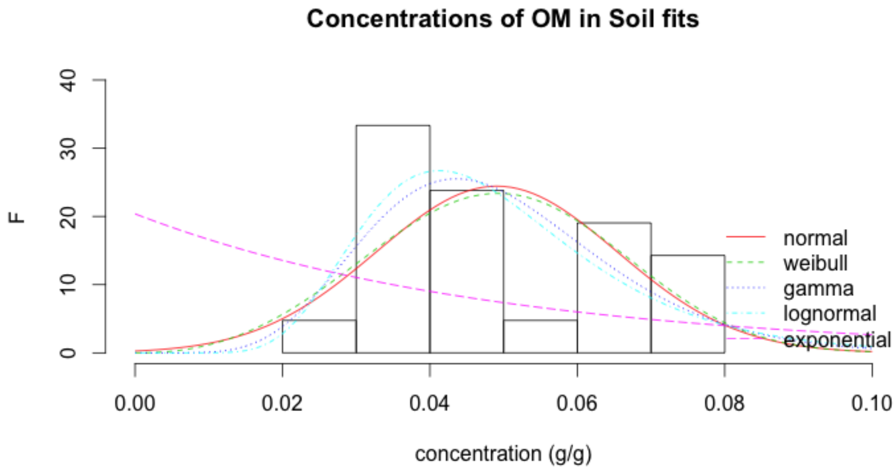


Figure C-1: Potential Distributions Overlaid on Histogram and CDF Plot for Floor Areas (m^2)



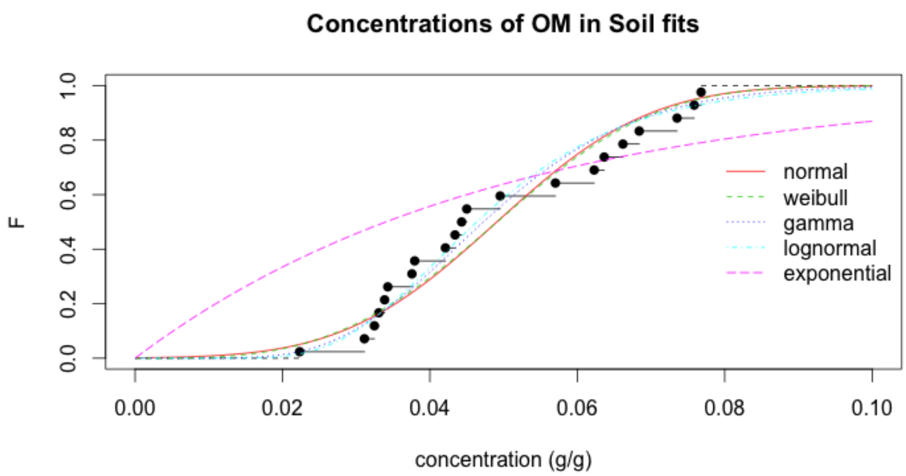
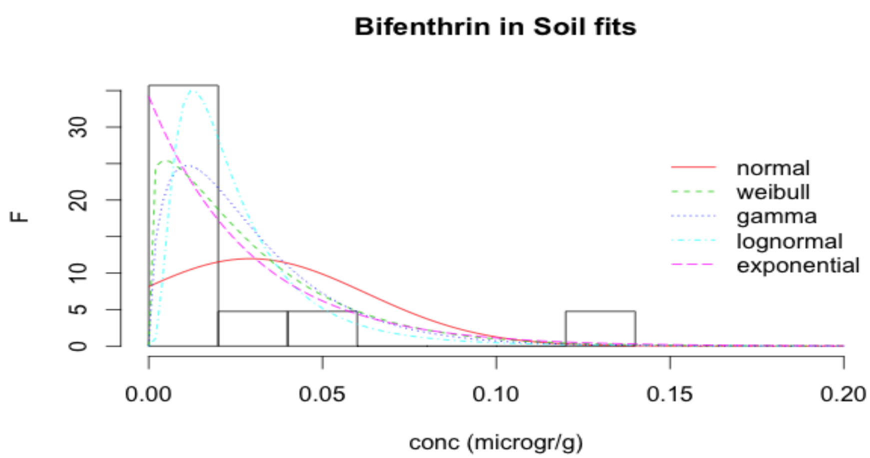


Figure C-2: Potential Distributions Overlaid on Histogram and CDF Plot for Concentrations of OM in Soil (g/g)



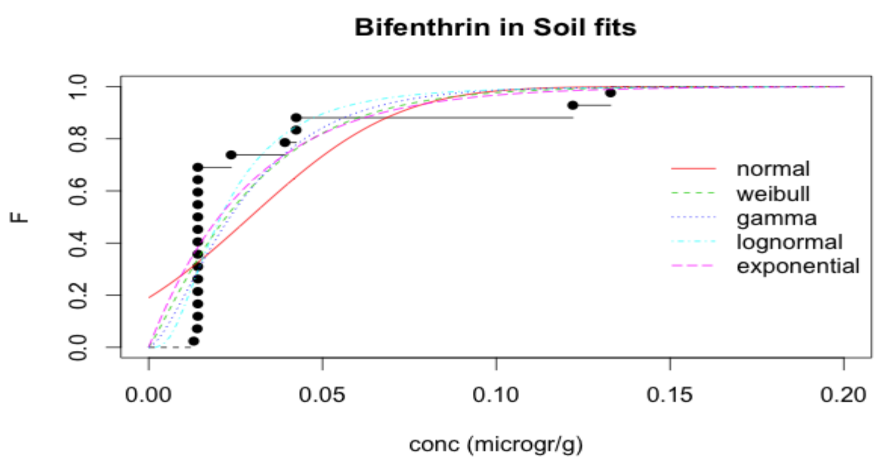


Figure C-3: Potential Distributions Overlaid on Histogram and CDF Plot for Concentrations of Bifenthrin in Soil (μg/g)

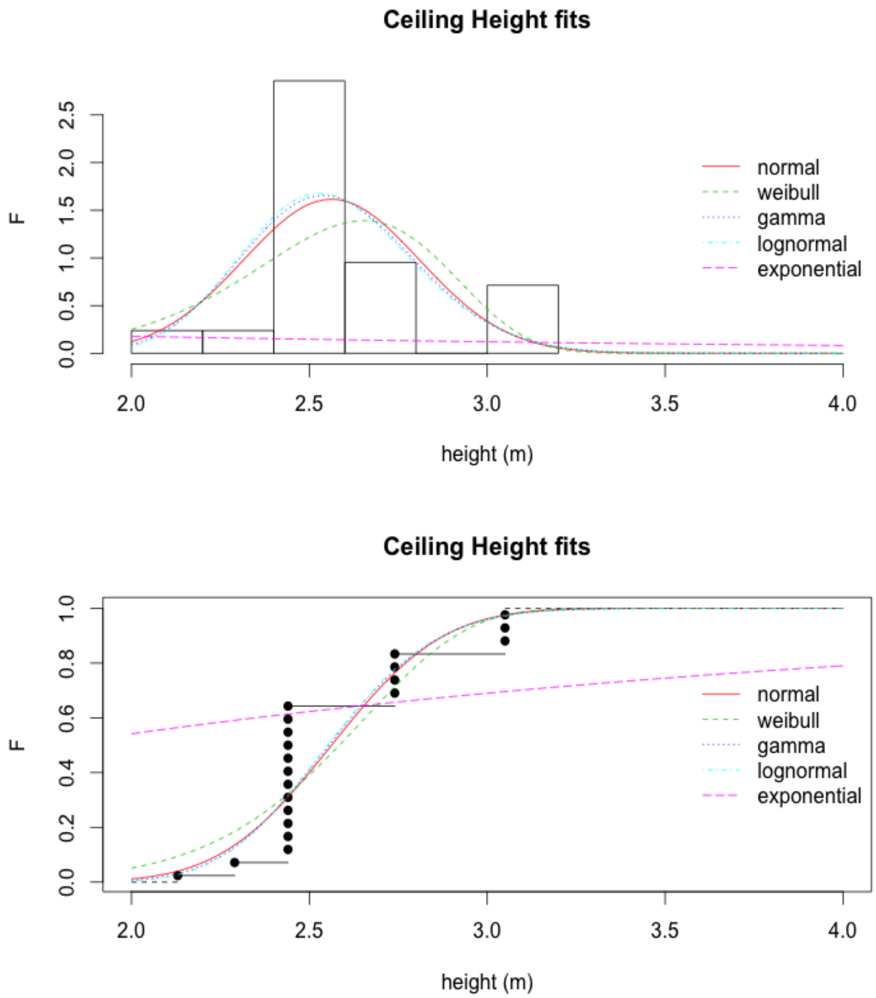


Figure C-4: Potential Distributions Overlaid on Histogram and CDF Plot for Ceiling Heights (m)

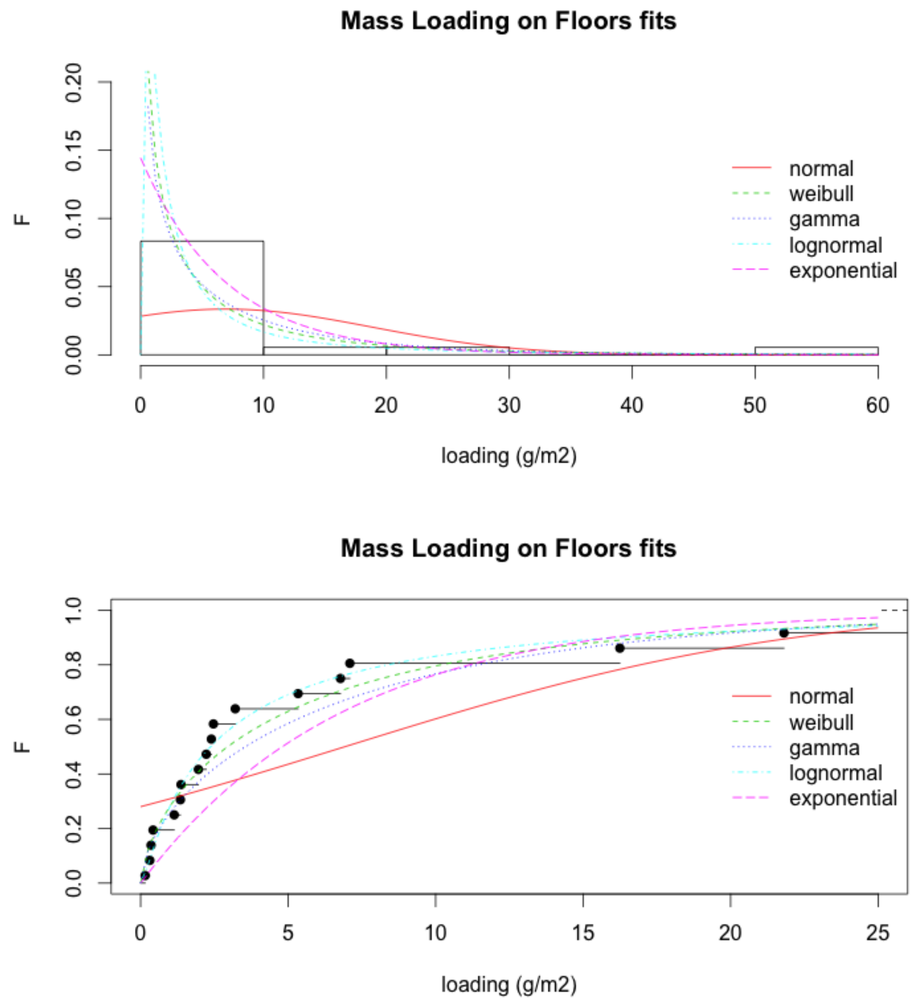


Figure C-5: Potential Distributions Overlaid on Histogram and CDF Plot for Mass Loading on Floors (g/m^2)

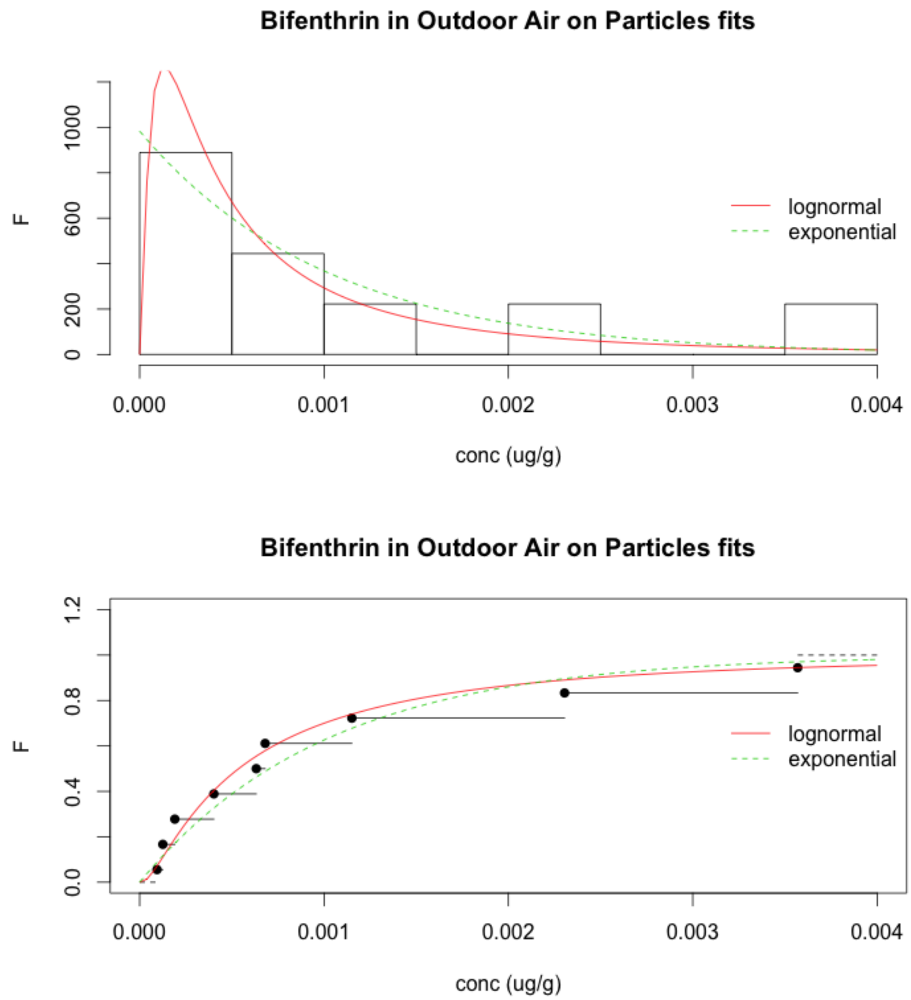


Figure C-6: Potential Distributions Overlaid on Histogram and CDF Plot for Bifenthrin in Outdoor Air on Particles (μg/m^3)

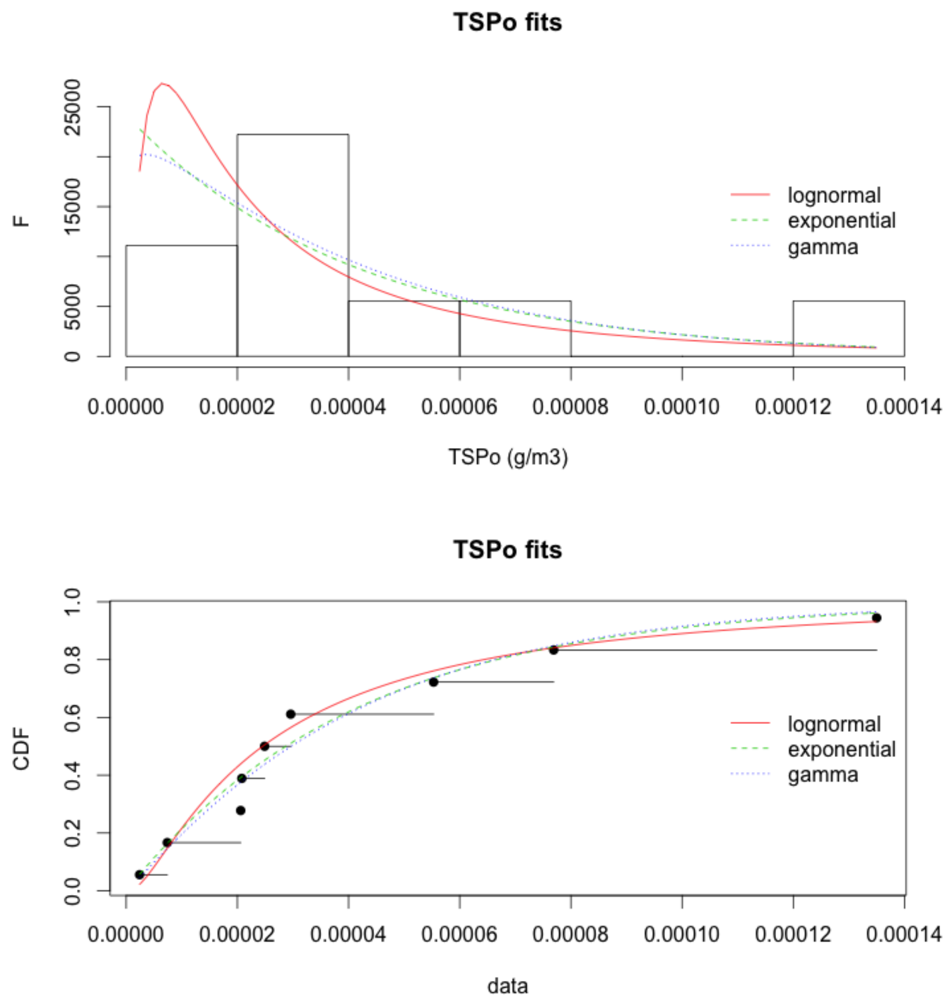
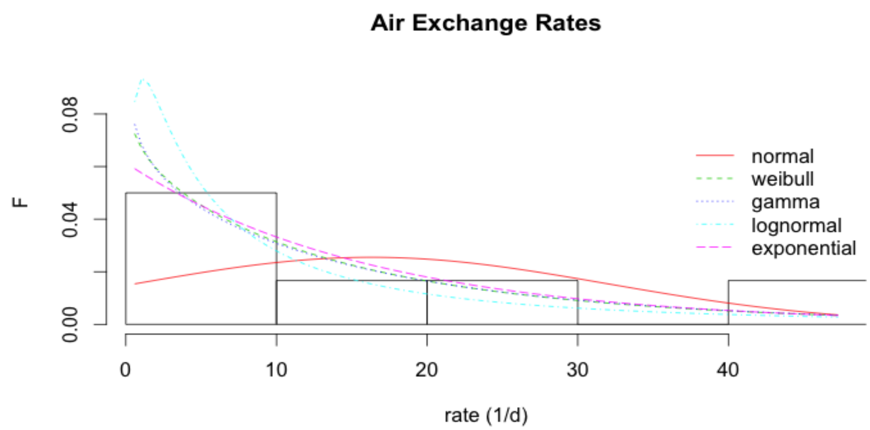


Figure C-7: Potential Distributions Overlaid on Histogram and CDF Plot for Outdoor Total Suspended Particles (g/m^3)



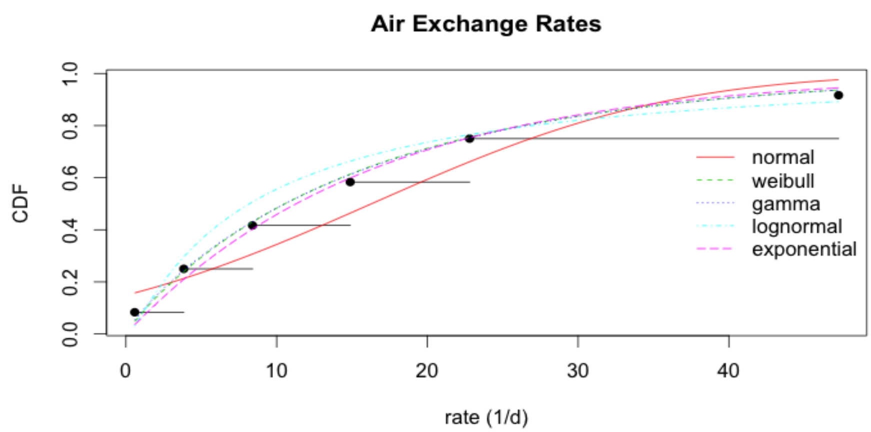


Figure C-8: Potential Distributions Overlaid on Histogram and CDF Plot for Air Exchange Rates (d^{-1})

Table C-1: Results of the K-S for Suspected Best-Fit Distributions

Variable	**Suspected Best- Fit Distribution**	*p-value*	**K-S Test** *Reject Distribution (Yes/No)?*
Floor Areas (m^2)	Lognormal	0.84	No
Concentrations of OM in Soil (g/g)	Lognormal	0.80	No
Concentrations of Bifenthrin in Soil (μg/g)	Lognormal	0.42	No
Ceiling Heights (m)	Normal	0.34	No
Mass Loading on Floors (g/m^2)	Lognormal	0.98	No
Bifenthrin in Outdoor Air on Particles ($\mu g/m^3$)	Lognormal	0.35	No
Outdoor Total Suspended Particles (g/m^3)	Lognormal	0.70	No
Air Exchange Rate (d^{-1})	Lognormal	0.63	No

Appendix D

Code for Execution of CART Models for Bifenthrin and Permethrin

Bifenthrin

```
#BINARY CART WITH NO CUTOFF- Below MDL ok; True ND labeled ND
attach(pestdataset_CART_upd2dec14_foruniv)
par(mfrow = c(1, 1))
#RPART
library(rpart)
library(rattle)
#use printcp( ) to examine the cross-validated error results, select cp associated with
minimum error, and place it into the prune( ) function.
#Alternatively, you can use the code fragment

#Outdoor air
bif_air_bin_belowmdlok_oda <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_air_bin_belowmdlok)
rpart.bif_air_bin_belowmdlok_oda <- rpart (bif_air_bin_belowmdlok ~
bif_month_lbsqmi_1buff + income_less21+ ed_hs+ avgyard_covered + meas_dist_ft
+ bif_soil_bin_belowmdlok + people_number + children_number +
farmworkers_number + fw_ppl_perc + catsdogspigs_out_only + catsdogspigs_inout
+ pesticideuse_inhome + shoes_removed_cont + clothes_changed_cont +
shower_cont ,data=pestdataset_CART_upd2dec14_foruniv, method="class",
minsplit=5, cp=0.001)
summary(rpart.bif_air_bin_belowmdlok_oda)
print(rpart.bif_air_bin_belowmdlok_oda)
fancyRpartPlot(rpart.bif_air_bin_belowmdlok_oda, uniform=TRUE, main="bifethrin
outdoor air Classification RPART method (not pruned)- noMDL cutoff")

#Prune and plot outdoor air
rpart.bif_air_bin_belowmdlok_oda$cptable
opt <-
rpart.bif_air_bin_belowmdlok_oda$cptable[which.min(rpart.bif_air_bin_belowmdlok
_oda$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_air_bin_belowmdlok_oda <-
prune(rpart.bif_air_bin_belowmdlok_oda, cp = opt)
summary(prune_rpart.bif_air_bin_belowmdlok_oda)
plot(prune_rpart.bif_air_bin_belowmdlok_oda, uniform=TRUE, main="Pruned
bifethrin in Outdoor Air- CLassification RPART method- noMDL cutoff")
#not a tree, only a root so used unpruned (only 2 cp values)
prune_rpart.bif_air_bin_belowmdlok_oda <-
prune(rpart.bif_air_bin_belowmdlok_oda, cp = 0.16666667 )
summary(prune_rpart.bif_air_bin_belowmdlok_oda)
```

```
fancyRpartPlot(prune_rpart.bif_air_bin_belowmdlok_oda, uniform=TRUE,
main="Pruned bifethrin in Outdoor Air- CLassification RPART method- noMDL
cutoff")


#Outdoor soil
bif_soil_bin_belowmdlok_ods <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_soil_belowmdlok)
rpart.bif_soil_bin_belowmdlok_ods <- rpart(bif_soil_bin_belowmdlok ~
bif_yumalb_yr + income_less21+ ed_hs+ avgyard_covered + meas_dist_ft +
bif_air_bin_belowmdlok + bif_air_bin_belowmdlok+ people_number +
children_number + farmworkers_number + fw_ppl_perc + catsdogspigs_out_only +
catsdogspigs_inout + pesticideuse_inhome + shoes_removed_cont + shower_cont +
clothes_changed_cont ,data=pestdataset_CART_upd2dec14_foruniv,
method="class", minsplit=5, cp=0.001)
summary(rpart.bif_soil_bin_belowmdlok_ods)
print(rpart.bif_soil_bin_belowmdlok_ods)
plot(rpart.bif_soil_bin_belowmdlok_ods)
text(rpart.bif_soil_bin_belowmdlok_ods, cex=0.5, pretty=30)
fancyRpartPlot(rpart.bif_soil_bin_belowmdlok_ods, main="bifethrin in Outdoor Soil-
Classification RPART method (not pruned)- noMDL cutoff")
text(rpart.bif_soil_bin_belowmdlok_ods,use.n=TRUE, all=TRUE, cex=0.6,
pretty=30)

#Prune and plot outdoor soil
rpart.bif_soil_bin_belowmdlok_ods$cptable
opt <-
rpart.bif_soil_bin_belowmdlok_ods$cptable[which.min(rpart.bif_soil_bin_belowmdl
ok_ods$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_soil_bin_belowmdlok_ods <-
prune(rpart.bif_soil_bin_belowmdlok_ods, cp = 0.001)
summary(prune_rpart.bif_soil_bin_belowmdlok_ods)
fancyRpartPlot(prune_rpart.bif_soil_bin_belowmdlok_ods, uniform=TRUE)


#Air infiltration
bif_dust_bin_belowmdlok_ai <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_ai <- rpart (bif_dust_bin_belowmdlok~
bif_yumalb_yr+ bif_month_lbsqmi_1buff + bif_yr_lbsqmi_1buff+
bif_air_bin_belowmdlok + income_less21+ ed_hs + house_age_10 +
avgyard_covered + meas_dist_ft + people_number + people_1000sqft +
children_number + children_1000sqft + farmworkers_number +
farmworkers_1000sqft + catsdogspigs_out_only + catsdogspigs_inout +
catsdogspigs_inout_1000sqft + pesticideuse_inhome + sqft + window_pane +
```

```
dw_cont + airfilt2 + cooling_months_number + cooling_type +
heating_months_number +
heating_type,data=pestdataset_CART_upd2dec14_foruniv,method="class",
minsplit=5, cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_ai)
print(rpart.bif_dust_bin_belowmdlok_ai)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_ai, uniform=TRUE, main="bifethrin
in Dust via Air Infiltration (not pruned)- CLassification RPART method- noMDL
cutoff")
text(rpart.bif_dust_bin_belowmdlok_ai, cex=0.8, pretty=30)

#Prune and plot air infiltration
plotcp(rpart.bif_dust_bin_belowmdlok_ai)
printcp(rpart.bif_dust_bin_belowmdlok_ai)
rpart.bif_dust_bin_belowmdlok_ai$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_ai$cptable[which.min(rpart.bif_dust_bin_belowmdlo
k_ai$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok_ai <-
prune(rpart.bif_dust_bin_belowmdlok_ai, cp = opt)
summary(prune_rpart.bif_dust_bin_belowmdlok_ai)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_ai, main=" Pruned bifethrin in
Dust via Air Infiltration- CLassification RPART method- noMDL cutoff")
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_ai)

#Air infiltration- remove agricultural applications
bif_dust_bin_belowmdlok_ai_removag <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_ai_removag <- rpart (bif_dust_bin_belowmdlok~
income_less21+ ed_hs + house_age_10 + avgyard_covered + meas_dist_ft +
people_number + people_1000sqft + children_number + children_1000sqft +
farmworkers_number + farmworkers_1000sqft + catsdogspigs_out_only +
catsdogspigs_inout + catsdogspigs_inout_1000sqft + pesticideuse_inhome + sqft +
window_pane + dw_cont + airfilt2 + cooling_months_number + cooling_type +
heating_months_number +
heating_type,data=pestdataset_CART_upd2dec14_foruniv,method="class",
minsplit=5, cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_ai_removag)
print(rpart.bif_dust_bin_belowmdlok_ai_removag)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_ai_removag, uniform=TRUE,
main="bifethrin in Dust via Air Infiltration (not pruned)- CLassification RPART
method- noMDL cutoff")
text(rpart.bif_dust_bin_belowmdlok_ai_removag, cex=0.8, pretty=30)

#Prune and plot air infiltration-remove agricultural applications
```

```
plotcp(rpart.bif_dust_bin_belowmdlok_ai_removag)
printcp(rpart.bif_dust_bin_belowmdlok_ai_removag)
rpart.bif_dust_bin_belowmdlok_ai_removag$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_ai_removag$cptable[which.min(rpart.bif_dust_bin_b
elowmdlok_ai_removag$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok_ai_removag <-
prune(rpart.bif_dust_bin_belowmdlok_ai_removag, cp = opt)
summary(prune_rpart.bif_dust_bin_belowmdlok_ai_removag)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_ai_removag, main=" Pruned
bifethrin in Dust via Air Infiltration- CLassification RPART method- noMDL
cutoff")
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_ai_removag)

 #Housing Structural Characteristics
bif_dust_bin_belowmdlok_struc <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_struc<- rpart (bif_dust_bin_belowmdlok ~
sqft_zillow + window_pane +house_age_10 + meas_dist_ft + carpet_yn +
cooling_type  + heating_type
,data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=5)
summary(rpart.bif_dust_bin_belowmdlok_struc)
print(rpart.bif_dust_bin_belowmdlok_struc)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_struc, uniform=TRUE,
main="bifethrin in Dust via Housing Structures (not pruned)- Classification RPART

#Prune and plot housing structural characteristics
fit$cptable[which.min(fit$cptable[,"xerror"]),"CP"]
plotcp(rpart.bif_dust_bin_belowmdlok_struc)
 printcp(rpart.bif_dust_bin_belowmdlok_struc)
rpart.bif_dust_bin_belowmdlok_struc$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_struc$cptable[which.min(rpart.bif_dust_bin_belowm
dlok_struc$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok_struc <-
prune(rpart.bif_dust_bin_belowmdlok_struc, cp = .1)
summary(prune_rpart.bif_dust_bin_belowmdlok_struc)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_struc, main="Pruned bifethrin
in Dust via Housing Structures- Classification RPART method-noMDLcutoff")
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_struc)

#Household behaviors
bif_dust_bin_belowmdlok_beh <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
```

```
rpart.bif_dust_bin_belowmdlok_beh<-rpart(bif_dust_bin_belowmdlok ~
mats_in_door + mats_out_door + pesticideuse_inhome + shoes_removed_cont +
clothes_changed_cont + shower_cont + dw_cont + airfilt2_cont +
cooling_months_number + heating_months_number + floor_cleaning_cont +
floor_cln_method + floor_cln_dryatall,
data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=5, cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_beh)
print(rpart.bif_dust_bin_belowmdlok_beh)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_beh, uniform=TRUE,
main="bifethrin in Dust via Behaviors (not pruned)- Classification RPART method-
MDLcutoff")
text(rpart.bif_dust_bin_belowmdlok_beh, cex=0.6, pretty=5000)

#Prune and plot household behaviors
plotcp(rpart.bif_dust_bin_belowmdlok_beh)
printcp(rpart.bif_dust_bin_belowmdlok_beh)
rpart.bif_dust_bin_belowmdlok_beh$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_beh$cptable[which.min(rpart.bif_dust_bin_belowmd
lok_beh$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok_beh <-
prune(rpart.bif_dust_bin_belowmdlok_beh, cp = .05)
summary(prune_rpart.bif_dust_bin_belowmdlok_beh)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_beh, main="Pruned bifethrin
in Dust via Behaviors- Regression RPART method-noMDLcutoff")
text(prune_rpart.bif_dust_bin_belowmdlok_beh, cex=0.6, pretty=5000)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_beh)


#Soil Track-in
bif_dust_bin_belowmdlok <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_sti <- rpart (bif_dust_bin_belowmdlok ~
bif_month_lbsqmi_1buff +sqft_zillow + carpet_yn + avgyard_covered +
mats_out_door+ mats_in_door + meas_dist_ft + bif_soil_bin_belowmdlok +
people_number + children_number + people_1000sqftz + children_1000sqftz +
farmworkers_number + farmworkers_1000sqftz + catsdogspigs_out_only +
catsdogspigs_inout + catsdogspigs_inout_1000sqftz + pesticideuse_inhome +
shoes_removed_cont + clothes_changed_cont + shower_cont
,data=pestdataset_CART_upd2dec14_foruniv, method="class", minsplit=4,
cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_sti)
print(rpart.bif_dust_bin_belowmdlok_sti)
```

```
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_sti, uniform=TRUE, main="bifethrin
in Dust via Soil Track-in (not pruned)- CLassification RPART method- noMDL
cutoff")
text(rpart.bif_dust_bin_belowmdlok_sti, cex=0.7, pretty=30)


#Prune and plot soil track-in
plotcp(rpart.bif_dust_bin_belowmdlok_sti)
printcp(rpart.bif_dust_bin_belowmdlok_sti)
rpart.bif_dust_bin_belowmdlok_sti$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_sti$cptable[which.min(rpart.bif_dust_bin_belowmdl
ok_sti$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok <- prune(rpart.bif_dust_bin_belowmdlok_sti,
cp = opt)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_sti, uniform=TRUE,
main="Pruned bifethrin in Dust via Soil Track-in - CLassification RPART method-
noMDL cutoff")

 #Soil Track-in- agricultural applications removed
bif_dust_bin_belowmdlok_sti_removag <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_sti_removag <- rpart (bif_dust_bin_belowmdlok ~
sqft_zillow + carpet_yn + avgyard_covered + mats_out_door+ mats_in_door +
meas_dist_ft + bif_soil_bin_belowmdlok + people_number + children_number +
people_1000sqftz + children_1000sqftz + farmworkers_number +
farmworkers_1000sqftz + catsdogspigs_out_only + catsdogspigs_inout +
catsdogspigs_inout_1000sqftz + pesticideuse_inhome + shoes_removed_cont +
clothes_changed_cont + shower_cont ,data=pestdataset_CART_upd2dec14_foruniv,
method="class", minsplit=4, cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_sti_removag)
print(rpart.bif_dust_bin_belowmdlok_sti_removag)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_sti_removag, uniform=TRUE,
main="bifethrin in Dust via Soil Track-in (not pruned)- CLassification RPART
method- noMDL cutoff")
text(rpart.bif_dust_bin_belowmdlok_sti_removag, cex=0.7, pretty=30)

#Prune and plot soil track-in- agricultural applications removed
plotcp(rpart.bif_dust_bin_belowmdlok_sti_removag)
printcp(rpart.bif_dust_bin_belowmdlok_sti_removag)
rpart.bif_dust_bin_belowmdlok_sti_removag$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_sti_removag$cptable[which.min(rpart.bif_dust_bin_
belowmdlok_sti_removag$cptable[,"xerror"]),"CP"]
opt
```

```
prune_rpart.bif_dust_bin_belowmdlok_sti_removag <-
prune(rpart.bif_dust_bin_belowmdlok_sti_removag, cp = opt)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_sti_removag, uniform=TRUE,
main="Pruned bifethrin in Dust via Soil Track-in - CLassification RPART method-
noMDL cutoff")
#Household dust-all factors combined
bif_dust_bin_belowmdlok_all <-is.factor
(pestdataset_CART_upd2dec14_foruniv$bif_dust_bin_belowmdlok)
rpart.bif_dust_bin_belowmdlok_all <- rpart (bif_dust_bin_belowmdlok ~
bifuse_dk_yes + bifuse_dk_excl+ bifuse_dk_own + sqft_zillow + bif_yumalb_yr+
bif_month_lbsqmi_1buff + bif_yr_lbsqmi_1buff+ carpet_yn + income_less21+
ed_hs+ avgyard_covered + meas_dist_mi + bif_soil_bin_belowmdlok +
bif_air_bin_belowmdlok + people_number + children_number + people_1000sqftz +
children_1000sqftz + farmworkers_number + farmworkers_1000sqftz +
catsdogspigs_out_only + catsdogspigs_inout + catsdogspigs_inout_1000sqftz +
catsdogspigs_in_only + catsdogspigs_in_only_1000sqftz + pesticideuse_inhome +
bifuse_dk_yes + bifuse_dk_excl + bifuse_dk_own + shoes_removed_cont +
clothes_changed_cont + shower_cont + dw_cont + airfilt2 + cooling_months_number
+ heating_months_number + mats_in_door+ mats_out_door + floor_cleaning +
floor_cln_method + floor_cln_dryatall + house_age_10  + sqft + window_pane +
airfilt2,data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=5,
cp=0.001)
summary(rpart.bif_dust_bin_belowmdlok_all)
print(rpart.bif_dust_bin_belowmdlok_all)
plot(rpart.bif_dust_bin_belowmdlok_all)
fancyRpartPlot(rpart.bif_dust_bin_belowmdlok_all, uniform=TRUE, main="bifethrin
in Dust ALL (not pruned)- Classification RPART method-MDLcutoff")
text(rpart.bif_dust_bin_belowmdlok_all, cex=0.6, pretty=5000)

#Prune and plot household dust- all factors combined
plotcp(rpart.bif_dust_bin_belowmdlok_all)
printcp(rpart.bif_dust_bin_belowmdlok_all)
rpart.bif_dust_bin_belowmdlok_all$cptable
opt <-
rpart.bif_dust_bin_belowmdlok_all$cptable[which.min(rpart.bif_dust_bin_belowmdl
ok_all$cptable[,"xerror"]),"CP"]
opt
prune_rpart.bif_dust_bin_belowmdlok_all <-
prune(rpart.bif_dust_bin_belowmdlok_all, cp = .001)
summary(prune_rpart.bif_dust_bin_belowmdlok_all)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_all, main="Pruned bifethrin in
Dust via ALL- Regression RPART method-noMDLcutoff")
text(prune_rpart.bif_dust_bin_belowmdlok_all, cex=0.6, pretty=5000)
fancyRpartPlot(prune_rpart.bif_dust_bin_belowmdlok_all)
```

Permethrin

```
#BINARY CART WITH NO CUTOFF- Below MDL ok; True ND labeled ND
attach(pestdataset_CART_upd2dec14_foruniv)
par(mfrow = c(1, 1))
#RPART
library(rpart)
library(rattle)
#use printcp( ) to examine the cross-validated error results, select cp associated with
minimum error, and place it into the prune( ) function.
#Alternatively, you can use the code fragment

#Outdoor air
perm_combo_air_bin_belowmdlok_oda <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_air_bin_belowmdlok)
rpart.perm_combo_air_bin_belowmdlok_oda <- rpart
(perm_combo_air_bin_belowmdlok ~ perm_yumalb_mon +
perm_month_lbsqmi_1buff + income_less21+ ed_hs+ avgyard_covered +
meas_dist_ft + perm_combo_soil_bin_belowmdlok + people_number +
children_number + farmworkers_number + fw_ppl_perc + catsdogspigs_out_only +
catsdogspigs_inout + pesticideuse_inhome + permuse_dk_yes + permuse_dk_own +
permuse_dk_excl + shoes_removed_cont + clothes_changed_cont + shower_cont
,data=pestdataset_CART_upd2dec14_foruniv, method="class", minsplit=5,
cp=0.001)
summary(rpart.perm_combo_air_bin_belowmdlok_oda)
print(rpart.perm_combo_air_bin_belowmdlok_oda)
fancyRpartPlot(rpart.perm_combo_air_bin_belowmdlok_oda, uniform=TRUE,
main="Permethrin outdoor air Classification RPART method (not pruned)- noMDL
cutoff")

#Prune and plot outdoor air
rpart.perm_combo_air_bin_belowmdlok_oda$cptable
opt <-
rpart.perm_combo_air_bin_belowmdlok_oda$cptable[which.min(rpart.perm_combo_
air_bin_belowmdlok_oda$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_air_bin_belowmdlok_oda <-
prune(rpart.perm_combo_air_bin_belowmdlok_oda, cp = opt)
summary(prune_rpart.perm_combo_air_bin_belowmdlok_oda)
plot(prune_rpart.perm_combo_air_bin_belowmdlok_oda, uniform=TRUE,
main="Pruned Permethrin in Outdoor Air- CLassification RPART method- noMDL
cutoff")
#not a tree, only a root so used unpruned (only 2 cp values)
prune_rpart.perm_combo_air_bin_belowmdlok_oda <-
prune(rpart.perm_combo_air_bin_belowmdlok_oda, cp = 0.3333333 )
summary(prune_rpart.perm_combo_air_bin_belowmdlok_oda)
```

```
fancyRpartPlot(prune_rpart.perm_combo_air_bin_belowmdlok_oda,
uniform=TRUE, main="Pruned Permethrin in Outdoor Air- CLassification RPART
method- noMDL cutoff")

#Outdoor soil
perm_combo_soil_bin_belowmdlok_ods <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_soil_belowmdlok)
rpart.perm_combo_soil_bin_belowmdlok_ods <-
rpart(perm_combo_soil_bin_belowmdlok ~ perm_yumalb_mon +
perm_month_lbsqmi_1buff + income_less21+ ed_hs+ avgyard_covered +
meas_dist_ft +  perm_combo_air_bin_belowmdlok + people_number +
children_number + farmworkers_number + fw_ppl_perc + catsdogspigs_out_only +
catsdogspigs_inout + pesticideuse_inhome +shoes_removed_cont + shower_cont +
clothes_changed_cont + permuse_dk_yes + permuse_dk_excl + permuse_dk_own
,data=pestdataset_CART_upd2dec14_foruniv, method="class", minsplit=5,
cp=0.001)
summary(rpart.perm_combo_soil_bin_belowmdlok_ods)
print(rpart.perm_combo_soil_bin_belowmdlok_ods)
plot(rpart.perm_combo_soil_bin_belowmdlok_ods)
text(rpart.perm_combo_soil_bin_belowmdlok_ods, cex=0.5, pretty=30)
fancyRpartPlot(rpart.perm_combo_soil_bin_belowmdlok_ods, main="Permethrin in
Outdoor Soil- CLassification RPART method (not pruned)- noMDL cutoff")
text(rpart.perm_combo_soil_bin_belowmdlok_ods,use.n=TRUE, all=TRUE, cex=0.6,
pretty=30)

#Prune and plot outdoor soil
rpart.perm_combo_soil_bin_belowmdlok_ods$cptable
opt <-
rpart.perm_combo_soil_bin_belowmdlok_ods$cptable[which.min(rpart.perm_combo
_soil_bin_belowmdlok_ods$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_soil_bin_belowmdlok_ods <-
prune(rpart.perm_combo_soil_bin_belowmdlok_ods, cp = 0.3333333)
summary(prune_rpart.perm_combo_soil_bin_belowmdlok_ods)
fancyRpartPlot(prune_rpart.perm_combo_soil_bin_belowmdlok_ods,
uniform=TRUE)

#Air infiltration
library(rpart)
perm_combo_dust_bin_belowmdlok_ai <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_ai <- rpart
(perm_combo_dust_bin_belowmdlok~ perm_month_lbsqmi_1buff +
perm_yumalb_mon + perm_combo_soil_bin_belowmdlok +
perm_combo_air_bin_belowmdlok + income_less21+ ed_hs + house_age_10 +
avgyard_covered + meas_dist_ft + people_number + people_1000sqft +
```

```
children_number + children_1000sqft + farmworkers_number +
farmworkers_1000sqft + catsdogspigs_out_only + catsdogspigs_inout +
catsdogspigs_inout_1000sqft + pesticideuse_inhome + sqft + window_pane +
dw_cont + airfilt2 + cooling_months_number + cooling_type +
heating_months_number +
heating_type,data=pestdataset_CART_upd2dec14_foruniv,method="class",
minsplit=5, cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_ai)
print(rpart.perm_combo_dust_bin_belowmdlok_ai)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_ai, uniform=TRUE,
main="Permethrin in Dust via Air Infiltration (not pruned)- CLassification RPART
method- noMDL cutoff")
text(rpart.perm_combo_dust_bin_belowmdlok_ai, cex=0.8, pretty=30)

#Prune and plot air infiltration
plotcp(rpart.perm_combo_dust_bin_belowmdlok_ai)
printcp(rpart.perm_combo_dust_bin_belowmdlok_ai)
rpart.perm_combo_dust_bin_belowmdlok_ai$cptable
opt <-
rpart.perm_combo_dust_bin_belowmdlok_ai$cptable[which.min(rpart.perm_combo_
dust_bin_belowmdlok_ai$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_dust_bin_belowmdlok_ai <-
prune(rpart.perm_combo_dust_bin_belowmdlok_ai, cp = 0.001)
summary(prune_rpart.perm_combo_dust_bin_belowmdlok_ai)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_ai, main=" Pruned
Permethrin in Dust via Air Infiltration- CLassification RPART method- noMDL
cutoff")
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_ai)

#Air infiltration- agricultural applications removed
library(rpart)
perm_combo_dust_bin_belowmdlok_ai_removag <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_ai_removag <- rpart
(perm_combo_dust_bin_belowmdlok~ perm_combo_soil_bin_belowmdlok +
perm_combo_air_bin_belowmdlok + income_less21+ ed_hs + house_age_10 +
avgyard_covered + meas_dist_ft + people_number + people_1000sqft +
children_number + children_1000sqft + farmworkers_number +
farmworkers_1000sqft + catsdogspigs_out_only + catsdogspigs_inout +
catsdogspigs_inout_1000sqft + pesticideuse_inhome + sqft + window_pane +
dw_cont + airfilt2 + cooling_months_number + cooling_type +
heating_months_number +
heating_type,data=pestdataset_CART_upd2dec14_foruniv,method="class",
minsplit=5, cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_ai_removag)
```

```
print(rpart.perm_combo_dust_bin_belowmdlok_ai_removag)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_ai_removag,
uniform=TRUE, main="Permethrin in Dust via Air Infiltration (not pruned)-
CLassification RPART method- noMDL cutoff")
text(rpart.perm_combo_dust_bin_belowmdlok_ai_removag, cex=0.8, pretty=30)

#Prune and plot air infiltration- agricultural applications removed
plotcp(rpart.perm_combo_dust_bin_belowmdlok_ai_removag)
printcp(rpart.perm_combo_dust_bin_belowmdlok_ai_removag)
rpart.perm_combo_dust_bin_belowmdlok_ai_removag $cptable
opt <- rpart.perm_combo_dust_bin_belowmdlok_ai_removag
$cptable[which.min(rpart.perm_combo_dust_bin_belowmdlok_ai$cptable[,"xerror"])
,"CP"]
opt
prune_rpart.perm_combo_dust_bin_belowmdlok_ai_removag <-
prune(rpart.perm_combo_dust_bin_belowmdlok_ai_removag, cp = 0.001)
summary(prune_rpart.perm_combo_dust_bin_belowmdlok_ai_removag)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_ai_removag,
main=" Pruned Permethrin in Dust via Air Infiltration- CLassification RPART
method- noMDL cutoff")


#Housing structural characteristics
perm_combo_dust_bin_belowmdlok_struc <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_struc<- rpart
(perm_combo_dust_bin_belowmdlok ~  avgyard_covered+ mats_in_door +
mats_out_door + sqft_zillow + window_pane +house_age_10 + + meas_dist_ft +
carpet_yn + cooling_type  + heating_type
,data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=4)
summary(rpart.perm_combo_dust_bin_belowmdlok_struc)
print(rpart.perm_combo_dust_bin_belowmdlok_struc)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_struc, uniform=TRUE,
main="Permethrin in Dust via Housing Structures (not pruned)- Classification
RPART method-MDLcutoff")

#Prune and plot housing structural characteristics
plotcp(rpart.perm_combo_dust_bin_belowmdlok_struc)
printcp(rpart.perm_combo_dust_bin_belowmdlok_struc)
rpart.perm_combo_dust_bin_belowmdlok_struc$cptable
opt <-
rpart.perm_combo_dust_bin_belowmdlok_struc$cptable[which.min(rpart.perm_com
bo_dust_bin_belowmdlok_struc$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_dust_bin_belowmdlok_struc <-
prune(rpart.perm_combo_dust_bin_belowmdlok_struc, cp = .01)
```

```
summary(prune_rpart.perm_combo_dust_bin_belowmdlok_struc)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_struc,
main="Pruned Permethrin in Dust via Housing Structures- Classification RPART
method-noMDLcutoff")
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_struc)


#Household behaviors
perm_combo_dust_bin_belowmdlok_beh <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_beh<-
rpart(perm_combo_dust_bin_belowmdlok ~ pesticideuse_inhome +
shoes_removed_cont +  clothes_changed_cont + shower_cont + dw_cont + airfilt2 +
cooling_months_number + heating_months_number + dusty.1 + floor_cleaning_cont
+ floor_cln_method + floor_cln_dryatall,
data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=5, cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_beh)
print(rpart.perm_combo_dust_bin_belowmdlok_beh)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_beh, uniform=TRUE,
main="Permethrin in Dust via Behaviors (not pruned)- Classification RPART
method-MDLcutoff")
text(rpart.perm_combo_dust_bin_belowmdlok_beh, cex=0.6, pretty=5000)

#Prune and plot household behaviors
#Prune back the tree to avoid overfitting the data. select a tree size that minimizes the
cross-validated error, the xerror column printed by printcp( ).
#use printcp( ) to examine the cross-validated error results, select cp associated with
minimum error, and place it into the prune( ) function.
#Alternatively, you can use the code fragment
fit$cptable[which.min(fit$cptable[,"xerror"]),"CP"]
plotcp(rpart.perm_combo_dust_bin_belowmdlok_beh)
printcp(rpart.perm_combo_dust_bin_belowmdlok_beh)
rpart.perm_combo_dust_bin_belowmdlok_beh$cptable
opt <-
rpart.perm_combo_dust_bin_belowmdlok_beh$cptable[which.min(rpart.perm_comb
o_dust_bin_belowmdlok_beh$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_dust_bin_belowmdlok_beh <-
prune(rpart.perm_combo_dust_bin_belowmdlok_beh, cp = 0.001)
summary(prune_rpart.perm_combo_dust_bin_belowmdlok_beh)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_beh, main="Pruned
Permethrin in Dust via Behaviors- Regression RPART method-noMDLcutoff")
text(prune_rpart.perm_combo_dust_bin_belowmdlok_beh, cex=0.5, pretty=5000)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_beh)
```

```
#Soil track-in
perm_combo_dust_bin_belowmdlok_sti <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_sti <- rpart
(perm_combo_dust_bin_belowmdlok ~ perm_month_lbsqmi_1buff +
perm_yumalb_mon + sqft_zillow + carpet_yn + avgyard_covered + mats_out_door+
mats_in_door + meas_dist_ft + perm_combo_soil_bin_belowmdlok +
people_number + children_number + people_1000sqftz + children_1000sqftz +
farmworkers_number + farmworkers_1000sqftz + catsdogspigs_out_only +
catsdogspigs_inout + catsdogspigs_inout_1000sqftz + pesticideuse_inhome +
shoes_removed_cont + clothes_changed_cont + shower_cont
,data=pestdataset_CART_upd2dec14_foruniv, method="class", minsplit=5,
cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_sti)

#Prune and plot soil track-in
print(rpart.perm_combo_dust_bin_belowmdlok_sti)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_sti, uniform=TRUE,
main="Permethrin in Dust via Soil Track-in (not pruned)- CLassification RPART
method- noMDL cutoff")
text(rpart.perm_combo_dust_bin_belowmdlok_sti, cex=0.7, pretty=30)
#note- this doesn't work with the setup minsplit=5, but can work with minsplit=3 for
exploratory purposes
#no pruning necessary

#Soil track-in- agricultural applications removed
perm_combo_dust_bin_belowmdlok_sti_removag <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_sti_removag <- rpart
(perm_combo_dust_bin_belowmdlok ~ sqft_zillow + carpet_yn + avgyard_covered +
mats_out_door+ mats_in_door + meas_dist_ft + perm_combo_soil_bin_belowmdlok
+ people_number + children_number + people_1000sqftz + children_1000sqftz +
farmworkers_number + farmworkers_1000sqftz + catsdogspigs_out_only +
catsdogspigs_inout + catsdogspigs_inout_1000sqftz + pesticideuse_inhome +
shoes_removed_cont + clothes_changed_cont + shower_cont
,data=pestdataset_CART_upd2dec14_foruniv, method="class", minsplit=5,
cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_sti_removag)

#Prune and plot soil track-in- agricultural applications removed
print(rpart.perm_combo_dust_bin_belowmdlok_sti_removag)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_sti_removag,
uniform=TRUE, main="Permethrin in Dust via Soil Track-in (not pruned)-
CLassification RPART method- noMDL cutoff")
text(rpart.perm_combo_dust_bin_belowmdlok_sti_removag, cex=0.7, pretty=30)
```

```
#note- this doesn't work with the setup minsplit=5, but can work with minsplit=3 for
exploratory purposes
#no pruning necessary

#Household dust-all factors combined
perm_combo_dust_bin_belowmdlok_all <-is.factor
(pestdataset_CART_upd2dec14_foruniv$perm_combo_dust_bin_belowmdlok)
rpart.perm_combo_dust_bin_belowmdlok_all <- rpart
(perm_combo_dust_bin_belowmdlok ~ sqft_zillow +
perm_yumalb_mon+perm_month_lbsqmi_1buff + carpet_yn + income_less21+
ed_hs+ avgyard_covered + meas_dist_mi + perm_combo_soil_bin_belowmdlok +
perm_combo_air_bin_belowmdlok + people_number + children_number +
people_1000sqftz + children_1000sqftz + farmworkers_number +
farmworkers_1000sqftz + catsdogspigs_out_only + catsdogspigs_inout +
catsdogspigs_inout_1000sqftz + catsdogspigs_in_only +
catsdogspigs_in_only_1000sqftz + pesticideuse_inhome + permuse_dk_yes +
permuse_dk_excl + permuse_dk_own + shoes_removed_cont +
clothes_changed_cont + shower_cont + dw_cont + airfilt2 + cooling_months_number
+ heating_months_number + mats_in_door+ mats_out_door + dusty + floor_cleaning
+ floor_cln_method + floor_cln_dryatall + house_age_10  + sqft + window_pane +
airfilt2,data=pestdataset_CART_upd2dec14_foruniv,method="class", minsplit=5,
cp=0.001)
summary(rpart.perm_combo_dust_bin_belowmdlok_all)
print(rpart.perm_combo_dust_bin_belowmdlok_all)
plot(rpart.perm_combo_dust_bin_belowmdlok_all)
text(rpart.perm_combo_dust_bin_belowmdlok_all, cex=0.7, pretty=300)
fancyRpartPlot(rpart.perm_combo_dust_bin_belowmdlok_all, main="Pruned Tree
Permethrin in House Dust via ALL methods- RPART METHOD")

#Prune and plot household dust-all factors combined
plotcp(rpart.perm_combo_dust_bin_belowmdlok_all)
printcp(rpart.perm_combo_dust_bin_belowmdlok_all)
opt <-
rpart.perm_combo_dust_bin_belowmdlok_all$cptable[which.min(rpart_perm_combo
_dust_bin_belowmdlok_all$cptable[,"xerror"]),"CP"]
opt
prune_rpart.perm_combo_dust_bin_belowmdlok_all <-
prune(rpart.perm_combo_dust_bin_belowmdlok_all, cp = 0.16666667)
summary(prune_rpart.perm_combo_dust_bin_belowmdlok_all)
fancyRpartPlot(prune_rpart.perm_combo_dust_bin_belowmdlok_all, main="Pruned
Tree Permethrin in House Dust via ALL methods- RPART METHOD")
```

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