LAND-ATMOSPHERE INTERACTIONS DUE TO ANTHROPOGENIC AND NATURAL CHANGES IN THE LAND SURFACE: A NUMERICAL MODELING STUDY

by

Zhao Yang

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Zhao Yang, titled Land-Atmosphere Interactions Due to Anthropogenic and Natural Changes in the Land Surface: A Numerical Modeling Study and recommended that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

___________________________________________ Date: 12/12/2016
Xubin Zeng

___________________________________________ Date: 12/12/2016
Francina Dominguez

___________________________________________ Date: 12/12/2016
Hoshin Gupta

___________________________________________ Date: 12/12/2016
Guo-Yue Niu

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

___________________________________________ Date: 12/22/2016
Dissertation Director: Xubin Zeng
STATEMENT BY AUTHOR

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SIGNED: Zhao Yang
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Abstract

Alterations to the land surface can be attributed to both human activity and natural variability. Human activities, such as urbanization and irrigation, can change the conditions of the land surface by altering albedo, soil moisture, aerodynamic roughness length, the partitioning of net radiation into sensible and latent heat, and other surface characteristics. On the other hand, natural variability, manifested through changes in atmospheric circulation, can also induce land surface changes. These regional scale land surface changes, induced either by humans or natural variability, can effectively modify atmospheric conditions through land-atmosphere interactions. However, only in recent decades have numerical models begun to include representations of the critical processes driving changes at the land surface, and their associated effects on the overlying atmosphere. In this work we explore three mechanisms by which changes to the land surface – both anthropogenic and naturally induced – impact the overlying atmosphere and affect regional hydroclimate.

The first land-atmosphere interaction mechanism explored here is land-use and land-cover change (LULCC) due to urban expansion. Such changes alter the surface albedo, heat capacity, and thermal conductivity of the surface. Consequently, the energy balance in urban regions is different from that of natural surfaces. To evaluate the changes in regional hydroclimate that could arise due to projected urbanization in the Phoenix–Tucson corridor, Arizona, my first study applied the Weather Research and Forecasting (WRF) with an Urban Canopy Model (UCM; which includes a detailed urban
radiation scheme) coupled to the Noah land surface model to this region. Land-cover changes were represented using land-cover data for 2005 and projections to 2050, and historical North American Regional Reanalysis (NARR) data were used to specify the lateral boundary conditions. Results suggest that temperature changes are well defined, reflecting the urban heat island (UHI) effect within areas experiencing LULCC, whereas changes in precipitation are less certain (statistically less robust). However, the study indicates the likelihood of reductions in precipitation over the mountainous regions northeast of Phoenix and decreased evening precipitation over the newly urbanized area.

The second land-atmosphere interaction mechanism explored here is irrigation which, while being an important anthropogenic factor affecting the local to regional water cycle, is not typically represented in regional climate models. In this (second) study, I incorporated an irrigation scheme into the Noah land surface scheme coupled to the WRF model. Using a newly developed water vapor tracer package (developed by Miguez-Macho et al. 2013), the study tracks the path of water vapor that evaporates from the irrigated regions. To assess the impact of irrigation over the California Central Valley (CCV) on the regional climate of the U.S. Southwest, I ran six simulations (for three dry and three wet years), both with and without the irrigation scheme. Incorporation of the irrigation scheme resulted in simulated surface air temperature and humidity that were closer to observations, decreased the depth of the planetary boundary layer over the CCV, and increased the convective available potential energy. The results indicated an overall increase in precipitation over the Sierra Nevada Range and the Colorado River Basin during the summer, with water vapor rising from the irrigated region moving mainly northeastward and contributing to precipitation in Nevada and Idaho. The results
also indicate an increase in precipitation on the windward side of the Sierra Nevada Range and over the Colorado River Basin. The former is possibly linked to a sea-breeze type circulation near the CCV, while the latter is likely associated with a wave pattern related to latent heat release over the moisture transport belt.

In the third study, I investigated the role of large-scale and local-scale processes associated with heat waves using the Modern Era-Retrospective Analysis for Research and Applications (MERRA) reanalysis, and evaluate the performance of the regional climate model ensemble used in the North America Regional Climate Change Program (NARCCAP) in reproducing these processes. The Continental US is divided into different climate divisions (following the convention of the National Climate Assessment) to investigate different mechanisms associated with heat waves. At the large scale, warm air advection from terrestrial sources is a driving factor for heat waves in the Northeast and Midwest. Over the western United States, reduced maritime cool air advection results in local warming. At the local scale, an antecedent precipitation deficit leads to the continuous drying of soil moisture, more energy being partitioned into sensible heat flux and acting to warm surface air temperatures, especially over the Great Plains. My analysis indicates that the NARCCAP simulated large-scale meteorological patterns and temporal evolution of antecedent local-scale terrestrial conditions are very similar to those of MERRA. However, NARCCAP overestimates the magnitude and underestimates the frequency of Northeastern and Midwestern US heat waves, partially due to anomalous heat advection through large-scale forcing.

Overall, the aforementioned studies show that utilization of new parameterizations in land surface models, such as the urban canopy scheme and the irrigation scheme, allow
us to understand the detailed physical mechanisms by which anthropogenic changes in the land surface can affect regional hydroclimate, and may thus help with informed decision making and climate adaptation/mitigation.

In addition to anthropogenic changes of the land surface, humans are of course affecting the overlying atmosphere. Currently, NARCCAP is the best available tool we have to help us understand the effects of changes greenhouse gas induced climate change at the regional scale. The regional climate models participating in NARCCAP are able to realistically represent the dominant processes associated with heat waves, including the atmospheric circulation changes and the land-atmosphere interactions that drive heat waves. This lends credibility, when analyzing the projections of these models with increased GHG emissions, to the assessment of changes in heat waves under a future climate.
Chapter 1: Introduction

1.1 Land-Atmosphere Interactions

The land surface and the atmosphere interact over a wide range of space and time scales to influence the global climate system (Sellers 1991). Land-atmosphere interactions involve the complex processes and feedbacks occurring at the land-atmosphere interface, including radiative, hydrological, and biogeochemical processes and exchanges of energy and matter between the land surface and its overlying atmosphere (Fernandez-Prieto et al. 2013).

1.1.1 Why do land-atmosphere interactions matter?

A scientific understanding of the land-atmosphere interface is important for describing, understanding and predicting the Earth system and its functioning as a whole (Suni et al. 2015). In addition, land-atmosphere interactions are important because humans can alter land surface conditions, which will in turn affect climate (Pielke and Zeng 1989; Pielke 2005; 2008). Critically, land-atmosphere interactions occur at the land-atmosphere interface where humans reside.

The importance of land-atmosphere interactions has increasingly been recognized (Seneviratne and Stöckli 2008). Global Climate Models (GCMs) are typically used to help us understand the complexity and effects of large-scale land-atmosphere interactions (Dirmeyer and Shukla 1996; Kleidon et al. 2000; Sacks et al. 2008). Perhaps the most influential studies of land-atmosphere interactions in the past decades are the ones that have identified hotspot regions where land-atmosphere interactions are strong (Koster et
Over the hotspots regions, soil moisture anomalies have strong impact on precipitation (Koster et al. 2004). Given the relative long-term memory of soil moisture (Seneviratne et al. 2006), these hotspots are of interest for possible improvements in seasonal predictability and strategies for design of ground-based and satellite-based soil moisture observation systems (Koster et al. 2004). However, large-scale land-atmosphere interaction studies often lack a quantitative analysis of the relevant physical processes.

1.1.2 Land-atmosphere interactions associated with changes in land surface characteristics

Several sensitivity studies have examined the impacts of modifying characteristics of the land surface on the overlying atmosphere (Otterman 1974; Charney et al. 1977; Otterman and Tucker 1985; Sud and Smith 1985; Laval 1986; Cunnington and Rowntree 1986; Chen 1994; Chase et al. 1996; Zeng et al. 1998). Characteristics of the land surface, including soil moisture (Emori 1998; Avissar and Chen 1994; Chen and Avissar 1994), albedo (Laval 1986; Cunnington and Rowntree 1986), leaf area index (Chase et al. 1996), distribution of roots and root depth (de Rosnay and Polcher 1998; Zeng et al. 1998) and aerodynamic roughness (Sud and Smith 1985; Sud et al. 1988) of the surface can exert strong impacts on the partitioning of available energy.

The partitioning of net radiation between sensible heat flux and latent heat flux at the surface can exert a significant effect on the atmosphere above (Pitman 2003). This is because less latent heat flux provides less water vapor to the atmosphere and tends to decrease cloudiness and precipitation, whereas less sensible heat flux tends to cool the
planetary boundary and reduce convection (Pitman 2003). Complex feedbacks within nature can enhance or reduce these energy fluxes (Meehl and Tebaldi 2004).

In terms of albedo, changes in surface albedo affect the absorption of shortwave radiation, and thus net radiation, sensible heat flux and latent heat flux (Cunnington and Rowntree 1986; Laval 1986). Charney (1977) proposed and showed that perturbations of albedo can lead to variations in precipitation. Comparing a spatially heterogeneous to a spatially uniform albedo, Lofgren (1995) found that high surface albedo cools the surface, reduces evaporative demand and allows the soil and vegetation to retain more moisture in high latitudes. Changes in the aerodynamic roughness length of the surface can also exert strong impacts on climate (Pitman 2003). While Sud et al. (1988) did not find significant changes to energy fluxes when the roughness length was reduced from 45 to 0.02 cm, they showed that reduction in roughness length can result in water vapor convergence and lead to a large increase in summer rainfall. Changes in the actual vegetation cover can alter the surface area of vegetation in contact with the atmosphere, and the corresponding balance between fluxes from the soil and vegetation (Pitman 2003). Decreased LAI can reduce canopy shading which increases net radiation at the soil surface and, as a result, increase soil evaporation; decreased LAI reduces transpiration and root water uptake, and consequently increases soil wetness and soil evaporation (adapted from Figure 3 in Pitman (2003)). Chase et al (1996) reported changes in global temperature and precipitation following a sensitivity study focused on LAI. Changes in root depth can dramatically alter the amount of soil water uptake for plants to transpire, and thereby affect canopy temperature and water vapor in the atmosphere (Pitman 2003).
In a modeling study using observed root distributions, Zeng et al. (1998) showed significant improvements to the water and energy balance.

1.1.3 Land-atmosphere interactions at different spatial scales

Any aspect of land surface characteristics which influences the energy partitioning and moistening of the boundary layer can affect local atmospheric conditions (Pielke 2001). The significance of these changes in regards to regional climate depends primarily on the spatial and temporal scale of the perturbation (Chen and Avissar, 1994). An example is the impact of irrigation on local climate. At the local scale, irrigation leads to slightly cooler but moister lower atmosphere over the irrigated region than the surrounding area (Pielke and Zeng 1989; Pielke 2001). The moistening of the lower atmosphere has been shown to be more important in increasing convective available potential energy (CAPE) than is the slight cooling achieved by decreasing CAPE (Pielke and Zeng 1989). As a result, local irrigation is likely to induce more precipitation over the same region (Barnston and Schickedanz 1984). On the other hand, Marcella and Eltahir (2014a) reported decreased precipitation over an irrigated area due to the cooling effect and collapse of the boundary layer.

At the regional scale, landscape heterogeneity can induce mesoscale atmospheric circulations (Segal et al. 1988; Pielke et al. 1991; Pielke 2001). Sea-breeze-type circulations induced by land-water contrasts can be expected over spatially heterogeneous regions (Pielke 1974; Pielke et al. 1991). Avissar and Liu (1996) found that the shape of the heterogeneity strongly influences the ability of mesoscale flows to concentrate CAPE and thereby impact thunderstorms. While numerous studies have investigated the impacts of land surface conversions on precipitation (Lyons et al. 1993; 1996; Clark and Arritt...
1995; Pielke et al. 1997; Emori 1998), contrasting results of changes in precipitation have been reported. For instance, Pielke et al. (1997) found an increase in precipitation when changing the natural land surface to a landscape with irrigated crops, shrubs, and natural short-grass prairie. On the contrary, Lyons et al. (1993; 1996) found that the replacement of native vegetation by agricultural crops reduces sensible heat flux and decreases rainfall. The regional importance of spatial and temporal variations in soil moisture and vegetation has also been studied extensively (Anthes 1984; Pan et al. 1996; Vidale et al. 1997). Pan et al. (1996) concluded that increases in soil moisture can enhance local rainfall when the lower atmosphere is thermodynamically unstable and relatively dry but decrease rainfall if the atmosphere is humid and lacks sufficient thermal forcing to initiate deep convection.

Global-scale land-atmosphere interactions studies typically use Global Climate Models (GCM) to investigate the sensitivity of climate to changes in land characteristics (Dirmeyer and Shukla 1996; Kleidon et al. 2000; Feddema et al. 2005; Sacks et al. 2008). For instance, Sacks et al. (2008) used the Community Atmosphere Model (CAM) to investigate the impact of irrigation and found that global irrigation cools the north mid-latitudes, but warms northern Canada by increasing the average annual temperature by 1 °C. The cooling impact is dominated by indirect effects like increasing cloud cover, rather than the direct impact of evaporative cooling (Sacks et al. 2008).

Landscape processes, from local to global scale, exert major influences on weather and climate (Pielke 2001). However, it is the regional scale land-atmosphere interactions that are of particular importance to informed decision making and adaptation planning,
and these yet remain to be well understood (Adam et al. 2015). In this study we focus on regional-scale changes in land-surface conditions and their effects on hydroclimate.

1.1.4 Land-atmosphere interactions associated with regional-scale land surface perturbation

Considerable evidence suggests the significance of land surface processes generated through regional scale land-surface perturbations, including reforestation (Bonan et al. 1992; Lean and Rowntree 1997), deforestation (Shukla et al. 1990; Feddema et al. 2005; Malhi et al. 2008), desertification (Xue 1997; Nicholson et al. 1998), and other types of land-use change (Chase et al. 1996; 2000; Gedney and Valdes 2000; Zhao et al. 2001a,b).

(a) Regional scale land surface changes due to natural variability

Natural variability of the global climate is driven largely by the El Nino-Southern Oscillation (ENSO), which impacts the tropics and many regions in the mid-latitudes (Ropelewski and Halpert 1986; Halpert and Ropelewski 1987). Ropelewski and Halpert (1986) reported precipitation and temperature anomalies over the North America associated with the ENSO. At the regional scale, natural variability can also act to modify land surface conditions (Chang and Wallace 1987; Whan et al. 2015). For instance, mid-level anticyclones are typically characterized by clear skies, subsidence and prolonged hot conditions – thereby drying the soil moisture at the surface (Xoplaki et al. 2003). As a result, more energy is partitioned into sensible heat flux due to the lack of soil moisture. The self-sustaining hot temperature accelerates the drying of soil moisture at the land
surface. In fact, most droughts are associated with persistent anticyclones (Seager et al. 2007; Seager and Vecchi 2010).

(b) Regional scale land surface perturbations through anthropogenic land use and land cover change

Humans have altered a significant fraction of the Earth’s surface via land use and land-cover change (LULCC) (Vitousek et al. 1997). Anthropogenic LULCC is likely to accelerate in the 21st century via human activities of urbanization, reforestation, deforestation or agricultural intensification, irrigation and so forth (Pitman 2003).

Recent research has suggested that the impacts of LULCC can be as significant as those caused by GHG induced climate change (Feddema et al. 2005; Georgescu et al. 2008). For instance, Feddema et al. (2005) performed climate simulations with different future land use scenarios and found that the impact of different land cover projections can alter the IPCC climate change simulations from those solely based on atmospheric composition change.

Therefore, understanding how the land surface impacts climate and identifying the physical processes associated with anthropogenic land surface change can help us to better define the role of land-atmosphere interactions in regional climate and, thereby, to possibly improve projections of future climate.

1.2 Objective

In this work, I look at specific examples of how changes in the regional scale land-use and land-cover and heterogeneity of land surfaces can lead to modifications of the regional hydroclimate in the US. The work presented in Appendix A, published in Earth Interaction (Yang et al. 2015), analyzes the effects of projected urbanization in Arizona
on the temperature and precipitation of the region. Appendix B, submitted to the Journal of Hydrometeorology, analyzes the effects of irrigation in the California Central Valley on the hydroclimate of the western US. Appendix C, to be submitted to Climate Dynamics, analyzes the role of both local land-atmosphere interactions and the large-scale environment in the formation of heat waves in the US.

Pielke (2005) suggested that all of the complex range of effects of the human disturbance of climate, including LULCC and GHG emissions, need to be considered to understand the human influence on climate. However, only very recently has the community begun to implement representations of anthropogenic modifications of the land surface into coupled land-atmosphere models. In this study, the application of an urban canopy scheme (Appendix A) and an irrigation scheme (Appendix B) allow us to understand the detailed physical mechanisms by which anthropogenic changes in the land surface can affect regional hydroclimate.

On the other hand, it is also important to understand how the large-scale environment interacts with local-scale processes through land-atmosphere interactions to affect regional climate. In Appendix C we show that the NARCCAP regional climate model ensemble over North America is able to realistically represent the dominant processes associated with heat waves, including the atmospheric circulation and the land-atmosphere interactions that drive heat waves. This lends credibility to the assessment of changes in heat waves in a future climate when analyzing the projections of these models with increased GHG emissions.
Chapter 2: Present Study

2.1 Urban Effects on Regional Climate: A Case Study in the Phoenix and Tucson “Sun Corridor”

Since the 1950s, the metropolitan region of Phoenix, Arizona, has been one of the fastest-growing urban areas in the US (Chow et al. 2012). It has undergone substantial land-use and land-cover change (LULCC) by transforming the agricultural and native semi-desert landscapes into urban areas. Under the most intense development scenario, Phoenix and Tucson are projected to grow into a unified urbanized area, developing into the so-called “Arizona Sun Corridor”.

In addition to the progressive increasing extent of urbanized regions, US urban areas have become progressively warmer due to the synergistic effects of global warming and the urban heat island effect. The extent to which the projected “Arizona Sun Corridor” might affect other aspects of the regional hydroclimate is not well understood. Therefore, the first goal of this work is to investigate the impact of the projected urbanized “Arizona Sun Corridor” on regional hydroclimate of the US southwest, and to evaluate the associated implications to water resources and energy consumption.

In this study, we used high-resolution simulations of 10 monsoon seasons (from 1991 to 2000) generated by the Weather Research Forecasting (WRF) Model under a current representation of land cover representing 2005 and a projected land cover representative of high rates of urban expansion representing 2050.
Our results suggest that urbanization will likely not impact the magnitudes of daily maximum temperatures but may result in significant increases in daily minimum (night time) temperatures over the urban corridor. However, both the time of daily maximum and minimum temperature are delayed, with about an hour for the maximum and 30 min for the minimum temperatures, resulting in longer periods of hotter temperatures. Such increased temperatures will likely increase the risk of heat-related health issues and even death (McGeehin and Mirabelli 2001).

We also examined the potential changes in 10-year climatological summertime precipitation due to urbanization. The analysis suggests a tendency for decreased precipitation over the mountainous higher elevations in the northern part of the domain and part of the newly urbanized region, but the results remain inconclusive, due to an inconsistency in tendencies indicated by two different tests (the Student’s t test and bootstrap test). Meanwhile, an analysis based on dominant wind direction did not provide statistically significant evidence in support of changes in precipitation patterns.

Overall, while our temperature results appear to be robust, our precipitation results must be treated as inconclusive. Due to the complex nature of convective precipitation in the southwest US, each precipitation event may have its unique intensity and location. Consequently, precipitation changes over the downwind region will likely not result in robust changes to spatial patterns. While this problem might potentially be solved by the use of a larger sample size, it seems unlikely.
2.2 Impact of Irrigation over the California Central Valley on Regional Climate

Irrigation, as an anthropogenic factor affecting the local to regional water cycle, can significantly affect land-atmosphere interactions from the local to the continental scale. Irrigation can modify climate mainly by changing the partitioning of available energy, increasing the latent heat flux and decreasing sensible heat flux, when compared to non-irrigated regions. However, irrigation is not typically represented in regional climate models. The irrigation modeling studies that have been conducted so far have reported impacts on different aspects of hydroclimate. While the cooling effect of daily maximum temperature is well established (Qian et al. 2013; Ozdogan et al. 2010; Sorooshian et al. 2011; Lo and Famiglietti 2013; Adegoke et al. 2010; Wei et al. 2013), the irrigation impact on precipitation is not so clear and seems to vary with the specific region of interest. Marcella and Eltahir (2014b) reported decreased precipitation over an irrigated area due to the cooling effect and the collapse of the boundary layer. In contrast, other studies have reported precipitation enhancement due to irrigation (Lo and Famiglietti 2013; DeAngelis et al. 2010; Qian et al. 2013).

The California Central Valley (CCV) accounts for one sixth of irrigated land in the US, and claims 20% of the Nation’s groundwater demand (Faunt 2009). Consequently, it is important to understand and properly represent CCV irrigation in the regional water cycle, especially considering the limited availability of water in southern California.

In this study, we incorporated an irrigation scheme into the Noah land surface model coupled with the WRF regional climate model, and calibrated the scheme for the agricultural area in the CCV. We conducted experiments with (denoted CNTL), and
without (denoted IRR), the irrigation scheme. Air temperature, dew point temperature and relative humidity at 2 m were evaluated against California Irrigation Management Information System (CIMIS) station data. Inclusion of the irrigation scheme resulted in improved simulation of the diurnal cycle of surface variables, e.g., surface air temperature, relative humidity. The daytime vertical profile suggests that local changes between IRR and CNTL exist mainly in the boundary layer. Simulations with irrigation have lower potential temperatures, higher humidity and higher instability in the boundary layer. Due to these changes, CAPE increases and LCL height decreases over the CCV. Despite these changes, differences in precipitation over the CCV are negligible – due to the fact that climatological precipitation in the summer is small over this region.

However, analysis of the IRR and CNTL simulations indicates that changes in integrated water vapor occur mainly downwind of the CCV region. Using water vapor tracers, we find that moisture that evaporates from the CCV is advected and precipitates northeast of the CCV. Strong divergence over the CCV leads to strengthened zonal moisture outflux, which generates increased precipitation over the windward side of the Sierra Nevada Range. While direct evaporation from irrigation contributes to precipitation northwest of the CCV, we also find changes in precipitation in the southwestern US (Colorado River Basin, CRB). Changes in precipitation over the CRB region are a result of indirect effects, not direct moisture advection.
2.3 Large and Local Scale Features Associated with Heat Waves in the United States and the Performance of the NARCCAP Ensemble in Simulating Heat Waves

Heat waves are often associated with detrimental socio-economic impacts on agriculture, energy consumption and even human life (Haines et al. 2006; Semenza et al. 2009). Furthermore, due to anthropogenic global warming, changes associated with temperature extremes are likely to have increasing impacts on society in the future (Seneviratne et al. 2012).

We analyze the interaction between local land-atmosphere interactions and large-scale processes in the development of heat waves in the US. Heat waves often involve two-way interactions between the local and large-scale features. For instance, local soil moisture deficits favor the formation of mid-level (500 hPa) high pressure; on the other hand, this mid-level high is often associated with clear skies, warm air advection and subsidence - which dries the soil. This positive feedback between the local and large-scale contributes to the formation of heat waves.

Many recent studies have unveiled the key processes involved in the formation of heat waves, including large scale meteorological patterns (LSMP) (Lau and Nath 2012; 2014; Cassou et al. 2005), interactions between the land and the atmosphere (Fischer et al. 2007a,b; Seneviratne et al. 2010) and soil moisture impacts (Whan et al. 2015; Hauser et al. 2016; Mueller and Seneviratne 2012; Lorenz et al. 2010). However, few studies have synergistically considered the role of large-scale meteorological patterns and antecedent surface conditions in causing heat waves in the US.
In this study – we used MERRA to understand both the large-scale and regional-scale conditions related to the formation of heat waves. We then analyzed NARCCAP Phase I simulations to evaluate the performance of the models in simulating heat wave events throughout the US.

Large-scale meteorological patterns associated with heat waves for each climate division have been analyzed in this study. A positive geopotential height anomaly at 500-mb is always present over the climate division when a heat wave occurs. This positive anomaly pattern is robust and has been shown in numerous studies (Lau and Nath 2012; 2014; Loikith et al. 2015), suggesting that this mid-level high has an important role in controlling the occurrences of heat waves across the US. Heat waves in different climate divisions are induced by different mechanisms. Specifically, the Northeast and Midwest are associated with warm air advection from terrestrial regions; the Southeast is also influenced by warm air advection but from the Gulf of Mexico; the Great Plains is associated with thermal lows and convergence at the low levels, indicating the importance of local contribution to heat waves; reduced advection of maritime cool air inland penetration, induced by large-scale meteorological patterns, are responsible for heat waves in the Northwest and Southwest.

The temporal evolution of antecedent 90-day surface variables in MERRA reveals that antecedent soil moisture, precipitation and evapotranspiration anomalies (with respect to climatological mean) and anomalies in latent and sensible heat flux are most obvious in transitional climate zones such as the Great Plains. In addition to the large scale synoptic forcing, large increases in sensible heat flux induced by antecedent soil moisture are also key to the formation of heat waves in the Great Plains region.
Our analysis indicates that large scale meteorological patterns are remarkably well represented in the NARCCAP, and the temporal evolution of antecedent terrestrial variables (including precipitation, evapotranspiration, and latent and sensible heat fluxes) are also well captured by the NARCCAP ensemble, lending confidence to our ability to utilize the NARCCAP ensemble for representing the physical processes associated with heat extremes throughout the US.

2.4 Future Works and Limitations

(a) Future works

The body of research presented in this work has opened the door to follow-up research projects that we are interested in pursuing. (1) In this work the NARCCAP ensemble has been shown to realistically represent heat waves, future projections of the NARCCAP ensemble (Phase II) can be studied to inform possible future changes in the extreme heat events. (2) Given the significant regional changes in precipitation by irrigating over the CCV, it is important to see the continental scale or global scale irrigation impacts on hydroclimate. More generally, we established a methodology to identify the direct and indirect impacts of a source regions with the application of the WRF tracer scheme. Such methodology is also applicable to many other situations.

(b) Limitations

This study has shown that regional land surface changes, either anthropogenically or naturally induced, can change the regional hydroclimate. However, there are certain aspects that are not considered in this study, and thus one should be cautious when interpreting the results.
First, they are uncertainties associated with the regional climate models. The models are developed to represent the dominant processes of interest, but quite often, there are unknown processes that might be important but yet still missing. In addition to these unknowns, uncertainties associated with the known processes are still quite significant. For instance, sub-grid scale precipitation is largely subject to parameterization, which can lead to poor representation in climate models. Tuning the model by calibration parameters, as we have done, is a way to solve it. But there is still significant work to be done in this area.

Additionally, we considered the single aspect of land surface changes in each study and concluded that land surface changes may affect the regional hydroclimate. However, it is not clear what would be the net effect of land surface changes when all these complex land surface changes are considered. For example, when both urbanization and irrigation are included, how would the hydroclimate change? In addition, other anthropogenic factors, such as aerosols, while being recognized as important to affect climate (Ramanathan et al. 2001), are not included in this analysis.

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Appendix A: Urban Effects on Regional Climate: A Case Study in the Phoenix and Tucson ‘Sun Corridor’

1 Introduction

Since 1950, the metropolitan region of Phoenix, Arizona, has been one of the fastest-growing urban areas in the United States (Chow et al. 2012). It has undergone substantial land use and land cover change (hereafter, LULCC) since World War II, by shifting economic priorities from a mostly agrarian lifestyle to an urbanized one. The most rapid development began around 1970, when the baby-boom generation reached adulthood, with a large number of job opportunities becoming available in the metropolitan area. By 2010, Phoenix (as the largest populated city in Arizona) had reached a population of 1.4 million, and an urban extension of 1,338.26 km$^2$ in 2010 (US Census, 2010). Meanwhile, Tucson has become the second-largest city with an area of 588 km$^2$ and a population of about 520,116 (US Census, 2010). With continuing development, both cities are projected to grow towards each other, developing into what has been called the “Arizona Sun Corridor”. By the year 2050, the “Sun Corridor” is projected to develop (under the most intense urbanization scenario) as shown in Figure 1, at the expense of agricultural and native semi-desert landscapes. Recent research has suggested that the impact of projected urbanization on summer-season local to regional temperature could be as significant as those induced by large scale-climate change (Georgescu et al. 2012).
Since 1970, summers in U.S. urban areas have been recorded as being progressively warmer under the synergistic effects of global warming and urban heat island effect (NCDC, http://www.ncdc.noaa.gov/cag/). The 2014 Climate Central report indicates that 57 out of 60 the largest cities U.S. cities had measurable growth in urban heat island effect over the period 2004 to 2013 (Climate Central, 2014). For Phoenix and Tucson, the mean temperatures are 1.8 °C and 0.22 °C warmer, respectively, than in their surrounding rural areas (Climate Central, 2014), and the temperature in the Phoenix urban core has been reported as being 2.2 °C higher compared to the surrounding area (Brazel et al. 2007). The most significant effect of urbanization of temperature (due to the urban heat island effect) has been found to occur at night, with minimum temperatures in Phoenix and Tucson being (on average) 3.8 °C and 1.3 °C respectively warmer than the surrounding rural area (Brazel et al. 2007). Svoma and Brazel (2010) reported that the daily minimum temperature is most strongly influenced by urbanization, with the mean minimum temperature during the urban period exceeding that of the pre-urban period by 4.4 °C.

In addition to the heat island effect, urbanization may also affect regional climate by changing local circulation and precipitation patterns. Evidence from many observational studies suggests that urbanization can bring about modifications to rainfall patterns over and downwind of cities (Burian and Shepherd 2005; Changnon et al. 1977; Shepherd 2005, 2006). In the early 1970s, the Metropolitan Meteorological Experiment (METROMEX) showed that urbanization can lead to increased precipitation during the summer season (Changnon et al. 1977; Huff and Vogel 1978), with about 5% - 25% increases in observed precipitation over and within 50-75 km downwind of the urban area.
(Changnon 1979; Changnon et al. 1981; Huff and Vogel 1978). Shepherd (2006) studied a 108-year precipitation historical data record for Arizona, and found statistically significant increases in mean precipitation of 11-14% in the Lower Verde basin (northeast of Phoenix) from a pre-urban (1895-1949) to post urban (1950-2003) period associated with the expansion of the Phoenix metro area. Studies also suggest that cities can also modify the diurnal distribution of precipitation. For instance, Balling and Brazel (1987) reported the more frequent occurrence of late-afternoon storms in Phoenix during recent years; however, they did not find evidence for significant changes in the mean precipitation amounts and frequencies during the entire summer monsoon season.

Several modeling studies have investigated the effects of urbanization on precipitation. Baik et al. (2001) investigated dry and moist convection forced by an urban heat island (UHI) effect using a 2-D, non-hydrostatic, compressible model, and concluded that increased urban heat island effect can decrease the time required for rainwater formation, while moving the horizontal location closer to the heating center. Craig and Bornstein (2002) found that the UHI can induce convergence and convection. Using the Weather Research and Forecast (WRF) model, Lin et al. (2011) found that the UHI can affects the location of thunderstorms and precipitation in northern Taiwan. Veerbeek et al. (2011) found that extreme rainfall over the cities of Beijing, Mumbai and Can Tho has been increasing, and suggested that significant changes in flood risk and precipitation levels will likely occur.

Over our region of interest, Georgescu et al. 2008 used the Regional Atmospheric Modeling System (RAMS) to simulate 3 different dry and 3 different wet years with land surface data circa 1973, 1992, and 2001 over the Phoenix metro region. They concluded
that the signal of increasing precipitation due to LULCC is present only during dry years. Georgescu et al. (2009a, 2009b) investigated the mechanism of precipitation enhancement and concluded that precipitation recycling, rather than the direct or indirect effect of the urbanization, may be responsible for the precipitation increase.

While numerous studies such as those mentioned above suggest an enhanced signature of precipitation over and downwind of metropolitan areas, there remain reasons to be skeptical. Precipitation anomalies in the La Porte station, Indiana, studied extensively in the METROMEX program, began to shift locale in the 1950s and then disappeared in the 1960s (Changnon 1980). Tayanç et al. (1997) found no evidence of urban effects on precipitation for four large cities in Turkey. And, a study of the Pearl River Delta of China actually reported reductions in precipitation (Kaufmann et al. 2008). Despite decades of work it remains unclear why the UHI can enhance precipitation in some regions while seemingly having no effect, or leading to decreases, in other regions.

This paper investigates temperature and precipitation variations over the state of Arizona that may arise due to projected urban expansion of the Phoenix-Tucson “Sun Corridor”. To understand the causes for potential temperature and precipitation changes over the urban and downwind regions, we employ a numerical modeling framework to examine the changes that may arise due to projected future expansion. We use the non-hydrostatic, compressible Weather Research and Forecasting model (WRF), and account for urban characteristics by incorporating an Urban Canopy Model (UCM). Our study is similar to the work of Georgescu et al. 2012 and 2013 in that we use the WRF+UCM to study the effects on regional climate in the “Sun Corridor” region. However, our goal is to examine the hydroclimate of the entire corridor region in detail, with our hypothesis
being that detailed representation of the hydroclimate of the region can lead to better characterization of the impacts of urbanization on precipitation. To this end, we use a high-resolution simulation that does not require a convective parameterization, and so is able to more accurately represent convective events during the monsoon season; i.e., our simulations are at a 2km resolution, while Georgescu et al. 2012 and 2013 use 20km resolution.

In the next section, we introduce the numerical model and experimental design. Section 3 presents and discusses results from two land use scenarios, and reports additional analysis regarding the potential impacts of LULCC on future water and energy demand variation. A summary and our conclusions appear in section 4.

2 Methodology

This study uses the WRF model to simulate regional climate with two different land use scenarios - one with historical observed land cover for 2005, and the other for projected future land cover. We perform simulation during the peak summer monsoon season (i.e., July and August) for each year from 1991 to 2000.

2.1 WRF Model and Configuration

The WRF model version 3.4 is coupled to a land surface and urban modeling system that aimed to address emerging issues in urban areas (Skamarock et al. 2008). Our experiment uses the Noah LSM to model the land surface (Chen and Dudhia 2001), thereby providing surface energy fluxes and surface skin temperatures that serve as the boundary conditions for the atmospheric model. While the original version of Noah LSM has a bulk parameterization for urban land use, our experiment uses a single layer urban canopy model (UCM) to better represent the energy fluxes and temperature within the
urban region. This single-layer urban canopy model, first developed by Kusaka et al. (2001) and further modified by Kusaka and Kumura (2004), consists of 2-dimensional symmetrical street canyons of infinite length, with treatment of momentum and energy that considers the canyon orientation and the diurnal variation of azimuth angle (Tewari et al. 2006). The UCM model estimates temperature, energy fluxes at roof, wall, and road surfaces, which later serve as lower boundary conditions for the atmospheric model. It is important to point out that the UCM does not include urban irrigation. Other parameterizations applied in this experiment were chosen based on the operational WRF simulations that are continuously produced at the University of Arizona during the monsoon season – all schemes, and in particular the microphysics scheme, have been chosen to optimally represent very heavy precipitation and winds associated with the strong to severe storms during the season (M. Leuthold 2013, personal communication). The parameterizations include the Morrison double-moment scheme for microphysics (Morrison et al. 2009), the CAM scheme which allows for aerosols and trace gases for longwave and shortwave radiation (Collins et al. 2004), the Eta surface layer scheme for the surface layer parameterization and the Noah land surface model for the land surface scheme (Chen and Dudhia 2001; Janjić 1996, 2002), the Mellor-Yamada-Janjic scheme for planetary boundary layer physics (Janjić 1990, 1996, 2002; Mellor and Yamada 1982), the Kain-Fritsch convective parameterization scheme (Kain 2004) for the outer domain, and no convective parameterization for the inner domain.

2.2 Study Domain

The study region mainly covers the state of Arizona, from latitude 30.7° N to 35.7° N, and longitude 115.2° W to 108.2° W. We use 2 nested domains with outer grid spacing
of 10 km and inner grid spacing of 2km (see Figure 1). The inner domain has 175 grid cells in the zonal direction and 190 grid cells in the meridional direction, and is chosen to correspond to the urban area and regions that may be affected by the urban corridor (i.e., including areas at least 75 km far from the urban border).

2.3 Land Use Representation

Land use characteristics for 2005 (hereafter, LULC_2005) were obtained directly from default MODIS land use data available in the WRF model. The projected land use characteristics for 2050 (hereafter, LULC_2050) are derived by combining three different datasets, under the most intense urbanization scenario:

1) SLEUTH data: A geospatial dataset describing a future current-trends scenario of unmanaged exponential growth of land use change into the year 2050 in the Santa Cruz Watershed (Tucson area) using the SLEUTH model (named as an acronym for its input data layer requirements: slope, land use, exclusion, urban extent, transportation and hillshade data), a fuzzy constrained cellular automata model that can predict potential future urban growth in a spatially explicit fashion. The dataset has a 30-m resolution, Universal Transverse Mercator projection (Zone 12), and was created using input from local government to establish areas to be excluded from growth. The scenario predicts the footprint of urban growth to approximately triple from 2009 to 2050, which is corroborated by local population estimates (Norman et al. 2012).

2) MAG: Raster imagery describing a future scenario for 2050, for the state of Arizona, developed by the Maricopa Association of Governments (MAG, 2005). MAG staff, working with the other Councils of Governments (COGs), used a
“red-dot” algorithm and input describing land ownership to establish areas to be excluded from growth, along with census information, to develop a “what if” scenario to see how the state could develop. Red dots represent housing units, which are expected to triple by 2050, from 2000, when the population is expected to hit 16 million (MAG, 2005).


The higher-resolution datasets (SLEUTH and MAG) were resampled to a uniform 250-m resolution to mimic the MODIS-derived NALC data, and then re-projected into Lambert Azimuthal Equal Area. The NALC data were reclassified to the MODIS 20-category land-use classification, where urban area is class #13. Urban classes from the MAG dataset for 2050 and the SLEUTH dataset for 2050 were overlain and superimposed into the MODIS-style dataset to mimic the highest resolution, most accurate future urban growth scenarios for the entire study area. This resulted in datasets describing land use/land cover for 2005 and in 2050 based on the modified IGBP-MODIS 20-category land-use classification. The datasets were converted from geospatial information systems (GIS) format into ASCII txt files, culminating in 43070 rows and 35000 columns of information, to be used as input to the WRF model. They were then super imposed on the default WRF MODIS 20-level classification scheme.

2.4 Lateral Boundary Conditions

The same climate forcings were used to drive the WRF model for the two different sets of land use data. The lateral boundary conditions were obtained from the North
American Regional Reanalysis (NARR) data (Mesinger et al. 2006). Initial soil moisture and temperature conditions were also derived from NARR data. NARR provides similar soil conditions when compared with the North American Land Data Assimilation System (NLDAS) soil moisture products (not shown). We simulated each of the years from 1991 to 2000, beginning on 1200 UTC 15 June and running through the end of August (1200 UTC 31 August) to cover the peak of the monsoon season in Arizona.

2.5 Observational Temperature Data

In section 3.4 we correlate urban temperatures with electricity load within Tucson and Phoenix to then be able to estimate the effect of future temperatures on electricity load under urban expansion. Near surface air temperatures collected by the Arizona Meteorological Network (AZMET) were used; AZMET provides meteorological and weather-based information for agriculture and horticulture in southern and central Arizona. The observation station for Tucson is located at 32°16’ N and 110°56’ W, very close to the city center. The station for Phoenix is the Phoenix Encanto site at 33°28’ N and 112°05’ W. Both sites are located within the urban region in the LULC_2005, and therefore provide a good representation of actual urban temperature. Both sites provide hourly air temperature, relative humidity, wind speed and etc (data available online at [http://ag.arizona.edu/azmet/](http://ag.arizona.edu/azmet/)).

The electric load data for Tucson were provided by the Tucson Electric Power (TEP), and for Phoenix by the Arizona Public Service (APS) and the Salt River Project (SRP). The electricity data were provided at one-minute time-step, and were aggregated to hourly time-step to correlate with the observed temperature data.
2.6 Calculation of Statistical Significance

To test for temperature and precipitation change, we performed statistical tests on their mean values. Since temperature and precipitation are highly auto-correlated, a de-correlation factor was incorporated into the statistical test using the following equation:

\[ z = \frac{\bar{\Delta} - \mu_\Delta}{(s/n)^{1/2}} \]

where \( \bar{\Delta} = \frac{1}{n} \sum_{i=1}^{n} \Delta_i = \bar{x}_1 - \bar{x}_2 \), \( n \) is the sample size; \( s \) is the sample variance of the \( n \) differences between \( x_1 \) and \( x_2 \); \( x_1 \) and \( x_2 \) are the sample data at each grid point under different landscape representations; and \( \mu_\Delta = 0 \) since the two sample means are assumed to be the same. To account for auto-correlation, we use the effective sample size \( n' \), formulated as:

\[ n' \approx n \frac{1 - \rho_1}{1 + \rho_1} \]

where \( \rho_1 \) is the lag 1 auto-correlation coefficient.

Statistical significance of the temperature and precipitation results was also analyzed using the bootstrap method, a useful approach for circumstances when sample sizes are small (Zoubir and Boashash 1998). This was performed as follows: 1) for each grid in each of the two landscape representations, the temperature and precipitation time series in LULC_2005 and LULC_2050 were resampled with replacement; 2) for each (re)sample, the corresponding mean and difference in mean were recorded; 3) steps 1) and 2) were repeated 1000 times; 4) if 97.5 % of the differences were found to be larger than 0, this was considered to represent a statistically significantly increase (similarly if
97.5% of the difference were less than 0 this was considered to represent a statistically significantly decrease, and otherwise representing no significant change).

3 Results

3.1 Evaluation of Model Performance

To evaluate model performance, simulations for the period 1991-2000 were compared with PRISM data (PRISM Climate Group, available online at http://prism.oregonstate.edu). Figure 2 shows that WRF simulation can reasonably downscale the spatial pattern of temperature and precipitation from the forcing NARR data. It captures the dipole pattern of precipitation distribution as well as the gradual decrease of temperature from the southwest to the northeast of the domain. After downscaling, WRF simulation tends to underestimate the domain averages for both temperature and precipitation, with WRF simulated temperature being about 0.91 °C cooler, and precipitation being about 38 mm (36%) less than PRISM for the simulated July-August period. Similarly, the original NARR data has less domain average precipitation as well (27.5mm less) but warmer average temperature (0.90 °C). Root mean square error (RMSE) of temperature is very close in both WRF (0.98 °C) and NARR (0.92 °C), but the precipitation in NARR was better with RMSE equals to 29.59 mm, comparing to 43.7 mm in WRF. Even though the WRF simulation underestimates precipitation as compared to NARR, it is important to note that precipitation in NARR is obtained from data assimilation and might not capture fine-scale precipitation features. On the other hand, due to the higher resolution in WRF, much finer details in the temperature and precipitation fields are represented. Moreover, WRF realistically captures the interannual variability of domain average temperature and precipitation.
(Figure 3), with correlation coefficient of 0.87 for temperature variation and 0.74 for precipitation variation. Even though the magnitudes of temperature and precipitation tend to be slightly lower than the PRISM data, the WRF simulations can be treated as credible, given that they realistically capture the spatial pattern and interannual variability.

3.2 Urban Impacts on Temperature

The effects of the urban heat island on temperature are shown in Figure 4. Daily mean, maximum and minimum temperature were obtained from hourly temperature data, and then were averaged respectively during the monsoon season to represent the seasonal mean, maximum and minimum temperature. On average, changes in the mean, maximum and minimum temperature over the urbanized area are +1.27 °C, -0.07°C and +3.09°C respectively. Difference in mean daily temperature between LULC_2050 and LULC_2005, averaged over 10 years of simulation, shows a statistically significant increase over the urbanized area. While the daily maximum temperature during the daytime is not significantly altered, the minimum temperature (occurring at night) over urbanized areas shows a significant increase. Changes in urban mean temperature and minimum temperature are found to be statistically significant, and can be explained by changes in surface thermal properties such as heat capacity and thermal conductivity. This explanation is supported by Figure 5 which shows the diurnal energy cycle averaged over the regions that are transformed from native vegetation in 2005 to urban in 2050 (newly urbanized). Transforming the natural land surface to urbanized results in more energy being stored as ground heat flux during the daytime from 7 am to 4 pm local time, whereas more positive ground heat flux appears during the night indicate more energy being released (warming the atmosphere) and leading to warmer air temperatures.
At the same time, urbanization results in decreased latent heat flux throughout the day, and the reduced evaporation limits the availability of atmospheric column water for convective processes. This result is similar to the findings of Georgescu et al. (2012). Meanwhile, our results show that greater sensible heat flux difference is positive during the night as expected, causing urban nighttime air temperatures to be larger. However, daytime sensible heat flux differences are negative. This, somewhat surprising result agrees with previous findings (Cao and Lin 2014), and can be attributed to the decrease in turbulent activity associated with the canyons of the urban canopy scheme. The vertical wind speed profile in the UCM follows that in previous literature Swaid (1993), with in-canyon wind speed being exponentially proportional to the wind speed above the canyon and helping to determine the heat flux exchange between the canyon wall, street and the air. When canyon wind speed is reduced due to the canyon structure following the exponential relation, the sensible heat flux from the wall and street to canyon is reduced as well, as reflected by the reduced sensible heat flux.

The diurnal temperature variation over the newly urbanized areas is also shown in Figure 5. The magnitude of difference in maximum and minimum temperature is consistent with the previous analysis. However the occurrence of maximum and minimum temperatures are delayed by about 1 hour and 30 minutes respectively. This means a longer duration of higher temperature during the day for LULC_2050, potentially leading to stress for the population residing in the urban areas.

The spatial pattern of sensible and latent heat flux is shown in Figure S.1 in supplemental file. Sensible heat flux is larger in the western part of the domain (in the lower desert), and smaller in the northeast (higher elevations). In contrast, latent heat flux
is greatest in the northeastern mountains and gradually decreases toward the western desert. The differences in the mean sensible heat flux due to urbanization indicates an increase in sensible heat flux (and decrease in latent heat flux) over Tucson and surroundings and the northeast high mountains, indicating a change in the partitioning of available energy. While increased sensible heat flux can indicate less stable conditions that could lead to increased precipitation, the reduced evapotranspiration results in less water available for convection; i.e., the two processes act in opposite directions. As we will show below, decrease in moisture availability leads to less precipitation.

3.3 Urban Impacts on Precipitation

3.3.1 Urban impacts on summer mean precipitation

Figure 6 shows the 10-year average summertime precipitation difference between LULC_2005 and LULC_2050. A pattern of decreasing precipitation dominates the northeastern mountainous part of the domain and some parts of the urban corridor. A student t test of the difference in daily mean precipitation at each grid cell suggests that this change is statistically significant. However the bootstrap test does not indicate a statistically significantly change, and so the results must be considered to be inconclusive.

Focusing on the diurnal cycle of precipitation, we analyze the precipitation differences for newly urbanized regions (Figure 7). The results indicate that while the timing of the peak in the diurnal cycle remains unchanged, there is a marked decrease precipitation (about 6%) during the late afternoon and early evening (1400 – 2100 LT). This suggests reduced precipitation in the newly urbanized areas likely due to reduced evapotranspiration.
To explain the fact that precipitation decreases over the northeastern part of the domain and parts of the urban corridor, we hypothesize that urbanization leads to a decrease in evapotranspiration (Figure S.1), so that less moisture is available to precipitate in the mountainous areas via regional precipitation recycling (similar to the suggestion by Georgescu et al. 2009b, 2012). It is important to point out, however, that monsoonal precipitation in the southwest US is highly variable both in terms of location and intensity. Figure S.2 (in supplemental file) shows the monsoon seasonal (July and August) accumulated precipitation for each year, from which it is clear that precipitation does not show a consistent pattern within the model domain for this 10-year timespan. Therefore, even if downwind precipitation is indeed changed due to urbanization, the small differences in location of precipitation from year to year would show up as negligible changes when averaging over time. Add to this the fact that different patterns of precipitation are associated with different dominant wind directions, and any signal can disappear simply due to changes in wind direction.

To dig further into this, we further characterized precipitation based on predominant wind patterns. Previous research defines the relative upwind and downwind region based on seasonal or annual dominant wind (Burian and Shepherd 2005; Georgescu et al. 2008; Shepherd 2006). However, moisture sources over the North American Monsoon (NAM) region vary daily. Moisture may come from Gulf of Mexico, the Pacific Ocean, the Gulf of California as well as terrestrial recycling from the Monsoon region (Hu and Dominguez 2014). Different sources of moisture are characterized by different synoptic conditions, and have different associated upwind and downwind regions. We therefore defined 8 flow regimes based on the hourly wind
direction at 500 hPa. If the wind direction in more than 50% of the urban area (in 2050) was coming from a particular direction, then that hour was assigned that particular wind direction. We compared the vertically integrated moisture flux to the wind at the 700 hPa and 500 hPa levels, and results indicate that the direction of the wind at 500 hPa level is more similar to the direction of the vertically integrated moisture flux.

Figure 8 shows the accumulated precipitation differences for different wind regimes. While the way to define wind flow regime is subjective, we checked the number of hours that fall into each category and found that (in total) more than 80% of simulated time steps fall in one of the 8 categories, during the remaining 20% of the time steps, the wind direction is spatially variable and does not fall into any category. The most frequent wind directions are southeasterly, southerly and southwesterly, accounting for 64% of all time steps. The least frequent wind patterns are northerly and northwesterly, accounting for less than 5% of the entire simulation period. This result agrees with previous studies analyzing wind flow patterns and the corresponding moisture sources during the monsoon season (Hu and Dominguez 2014). The results show high spatial heterogeneity with regions of increasing precipitation and regions of decreasing precipitation. The decrease in precipitation seen in the mean (Figure 6b) seems to arise due to precipitation differences when the wind comes from the southeast and the south, but again, the results are noisy and not statistically significant (see Figure S.3 in supplemental file). Even when analyzed based on the dominant flow conditions, the results remain inconclusive.

3.3.2 Urban Impacts on Precipitation Occurrences

Previous research suggests that urban regions may initiate convection (Balling and Brazel 1987; Changnon and Westcott 2002; Takahashi 2003), and hence it is reasonable
to expect a larger number of convective days in urban regions, as compared to the native land cover. Here we define a precipitation day when more than 0.1 mm/day of precipitation falls over 20% or more of the urban area in one day. However, these area and precipitation thresholds are subjective, so we tested different thresholds of precipitation and areal cover. Depending on whether the day is designated as a precipitation (p) or not (n) in the current (c) and future (f) land cover experiments, we have 4 possible categories: 1) rains in both LULC_2005 and LULC_2050, (cpfp), 2) no rain in LULC_2005 and rains in LULC_2050, (cnfp), 3) rains in LULC_2005 and no rain in LULC_2050, (cpfn), 4) doesn’t rain in either, (cnfn). Precipitation days each of the 4 categories are shown in Table 1. By comparing cnfp and cpfn, we can determine whether more precipitation days occur due to urbanization. As expected in an arid region, most days are “not precipitation” days in both LULC scenarios. When looking at the other cases, our results suggest a reduction in precipitation days due to urbanization (6 out of 9 cases), however, the results depend on the precipitation and areal cover thresholds used.

3.4 Urban Impacts on Water and Energy Demand

Our results suggest that projected expansion of the urban corridor in the Phoenix-Tucson area (as simulated by WRF) may affect both temperature and precipitation, which can be expected to affect water and energy demand in the region. The Arizona Department of Water Resources (ADWR) provides water demand information and assessments for each active management area (i.e., area that heavily relies on the groundwater supply). The goal is to ensure that, by the year 2025, groundwater be withdrawn at a rate that equals the recharge. Tucson and Phoenix are located in the Tucson Active Management Area (i.e. TAMA) and Phoenix Active Management Area.
(PAMA), respectively. Historically, Tucson municipal water demand has increased by 68% from \(1.39 \times 10^8 \text{ m}^3 \text{ yr}^{-1}\) in 1985 to \(2.33 \times 10^8 \text{ m}^3 \text{ yr}^{-1}\) in 2006. During the same period, Phoenix municipal water demand grew by 76%, increasing from \(7.82 \times 10^8 \text{ m}^3\) to \(1.38 \times 10^9 \text{ m}^3\) per year. The total water demand increase for both cities was roughly 75%. At the same time, Tucson’s area grew by 124% and Phoenix’s area grew by 50% - the area of the two cities combined grew by 68%. This indicates that during this period, the water demand for the two cities combined grew almost linearly with area (with Tucson growing more but conserving more water per area than Phoenix). Based on these estimates, the land use projections used in this study (that urban extent in 2050 is about 7 times larger than in 2005), and an assumption that water usage intensity remains the same in year 2050 as in 2005, we estimate that water demand will grow (linearly) to around \(1.12 \times 10^{10} \text{ m}^3\) for the entire corridor. Bear in mind that this urban projection is made by assuming a scenario of high rates urban expansion, and it is not likely that this water demand will be easily satisfied, especially given the water-limited nature of the State of Arizona.

Groundwater is an important water source in the State of Arizona, accounting for 64% of water supply in TAMA and 31% in PAMA in 2006. The ADWR projections of future water demand are based on population growth rate and water use, with the assumption that when the full utilization of all other water sources cannot meet the demand, groundwater can be utilized to meet the remainder. In their highest water demand scenario, municipal water demands are \(3.80 \times 10^8 \text{ m}^3\) and \(2.59 \times 10^9 \text{ m}^3\) for TAMA and PAMA respectively, requiring groundwater overdrafts in 2025. Our estimates indicate a much larger water demand by 2050 (under the assumptions stated above),
suggesting there will simply not be enough water to sustain that level of urbanization. Thus, urban growth to the extent portrayed by LULC_2050 is probably unsustainable, with water being an important limitation to future urbanization unless alternative sources are found.

Meanwhile, temperature increases within the urban area (along with the greenhouse gas-induced global climate change) are likely to increase energy demands for electricity cooling needs (Georgescu et al. 2013). Cooling demands in the urban areas are known to account for more than 50% of the total electricity demand, with this ratio climbing to as high as 65% during the hot season evening hours in semi-arid urban environments (Salamanca et al. 2013). Here we use electric load data for Tucson and Phoenix and assume the ratio of air conditioning (AC) consumption to total electric load as following the diurnal pattern as shown in Salamanca et al., 2013. The data are provided at the intra-daily timescale by Tucson Electric Power for Tucson and Arizona Public Service (APS) and Salt River Project (SRP) for Phoenix. The diurnal AC consumption in each city is obtained by multiplying the diurnal total electric load to the corrected ratio. Figure 9 shows that the AC consumption follows a very similar diurnal pattern to the diurnal temperature observed within the urban area for the same period.

To project AC consumption under warmer temperatures, temperature and electric load were fitted to a polynomial function (with linear correlation coefficient of 0.85 for Tucson and 0.85 for Phoenix); the results clearly suggest that temperature plays a significant role in influencing the AC consumption (see Figure 10). Then for each hour during the day, the increased energy load due to UHI-induced temperature increase can be obtained from the fitted function. Consequently, the projected future total AC
consumption accounts for increase in temperature as well as the urban expansion. Even though there are many other factors that may affect the energy consumption, it is safe to assume that areal enlargement and temperature are likely to be among the most important factors affecting future AC consumption. Considering larger area and temperature simultaneously, the projection of future additional AC consumption demand for Tucson and Phoenix is shown in Figure 11. Overall, the areal enlargement due to urban expansion appears to be the dominant factor affecting energy consumption in the future.

4 Conclusions

This study has examined the climatological effects associated with potential expansion of the Phoenix-Tucson urban corridor on summer monsoonal (July and August) climate in Arizona. It needs to be emphasized that only the impact of urbanization is studied here, while the expected global warming effect from 1991 to 2050 is not considered. Given that the Phoenix metropolitan area has been one the most rapidly developing areas in the United States during the past 30 years, and that the Phoenix-Tucson ‘Sun’ Corridor is still expected to add another 5 to 6 million inhabitants from 2000 to 2030 (US Census, 2005), it is useful for planners to understand how urbanization can affect the hydroclimate of the region. We used high-resolution simulations of 10 monsoon seasons (from 1991 to 2000) generated by the WRF model under a current representation of land cover (LULC_2005) and a projected land cover representative of high rates of urban expansion (LULC_2050).

Our results suggest that urbanization will likely not impact the magnitudes of daily maximum temperatures, but may result in significant increases in daily minimum (night time) temperatures over the urban corridor. This agrees with previous research indicating
that the urban heat island is mainly a nocturnal phenomenon. Accordingly the increases in daily mean temperature are mainly due to increased nighttime temperatures. These results agree with Georgescu et al., (2013). However, both the daily maximum and minimum temperature are delayed, with about an hour for the maximum and 30 minutes for the minimum temperatures resulting in longer periods of hotter temperatures. Such increased temperatures will likely increase the risk of heat related health issues and even death (McGeehin and Mirabelli 2001). Of course, it is possible that implementation of ‘cool-roof’ technology could help to reduce the UHI phenomenon providing a potential solution to relieve the impact on temperature (Georgescu et al. 2013).

Surprisingly, our energy diurnal cycles over the newly urbanized region suggest that sensible heat flux will increase during the nighttime and decrease during the day (due to sensible heat flux calculations in the urban canopy model, as explained earlier). Meanwhile latent heat fluxes are likely to decrease dramatically throughout the day, resulting in less evaporation over urban regions and downwind mountainous areas. The overall effect of urbanization is likely to be less moisture available for convection. Overall, our results indicate that the ground heat flux difference will be negative during the day and positive during the night, indicating energy storage within the soil column during the day and release to the atmosphere during the night.

We also examined the potential changes in 10-year climatological summertime precipitation due to urbanization. Decrease in precipitation over the mountainous higher elevations in the northern part of the domain and part of the newly urbanized region remains inconclusive, due to the inconsistency between the Student’s t test and bootstrap test. However, an analysis based on dominant wind direction did not provide statistical
significant evidence for changes in precipitation patterns. These results are consistent with those of Georgescu et al. 2012. However, unlike Georgescu et al. 2012, our results are much more spatially heterogeneous (a result of using very high resolution to conduct the simulations) and reductions are only seen in the mountainous northeastern part of the domain and part of the urbanized region.

Overall, while our temperature results appear to be robust, our precipitation results must be treated as inconclusive. Due to the complex nature of convective precipitation in the southwest US, each precipitation event has its unique intensity and location. Consequently, precipitation changes over the downwind region will likely not result in robust changes to spatial patterns. While this problem might potentially be solved by use of a larger sample size, it seems unlikely. We hypothesize that because the ambient air is very dry, impacts of urbanization on energy partitioning at the surface will not result in significant changes in precipitation because there is simply not enough available specific humidity. In contrast, similar research conducted in Tokyo, Japan, where summertime relative humidity is usually above 70%, reported increased precipitation over the metropolitan area (Kusaka et al. 2014).

Finally, we developed rough estimates of future water and energy demand based on urban expansion and temperature change. Assuming that increase in urban area is the main factor influencing the water demand, our estimates indicate that about 7 times the current water supply would be needed to sustain an urban scale like LULC_2050, which would require extensive access to groundwater storage. This suggests that projected urban expansion to the extent represented by LULC_2050 will be very difficult to achieve without access to new sources of water. Meanwhile, energy supplies will have to
be expanded to meet future air conditioning needs to deal with the longer durations of high day and nighttime temperatures.

There are, of course, limitations to our study that must be accounted for in any analysis involving urban planning. In particular, we did not consider the impacts of aerosol, even though the role of aerosols in urban environments will likely be an important factor. Other limitations include the lack of consideration of irrigation effects in the land surface representation, which can be expected to have a significant impact on the water and energy budget over the region. Irrigation over urban areas can actually increase the latent heat flux while decreasing the sensible heat flux, leads to the so-called “oasis” effect (Georgescu et al. 2011) and potentially contributing to changes in precipitation. It is important to emphasize that our study does not include urban irrigation, which could be important in cities like Phoenix and Tucson. To evaluate the potential impact of urban irrigation in our results, we performed a sensitivity study with a rough characterization of urban irrigation where soil moisture was set to saturation over 15% of the urban area. Our results show that with-and without urban irrigation, temperature increases over the newly urbanized region and precipitation decreases over the entire domain and in particular over the newly urbanized region. While including urban irrigation generates a weaker response (there is more precipitation in the urban irrigation case), there is still an overall decrease in precipitation due to increased urbanization. Another important factor affecting regional precipitation may be precipitation recycling (Georgescu et al. 2009b). Studies exploring these and other effects will be reported in future papers.
Acknowledgement

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Reference


——, 2002: Nonsingular implementation of the Mellor–Yamada level 2.5 scheme in the NCEP Meso model. NCEP office note, 437, 61.


Tables

Table 1: number of days in each category (as discussed in the text) with regard to whether it was convective day or not in each land cover representation.

<table>
<thead>
<tr>
<th>precipitation threshold (mm/day)</th>
<th>area threshold (%)</th>
<th>cnfn</th>
<th>cpfn</th>
<th>cnfp</th>
<th>cpfp</th>
<th>More Precip. in Future LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>20</td>
<td>305</td>
<td>21</td>
<td>23</td>
<td>241</td>
<td>T</td>
</tr>
<tr>
<td>0.5</td>
<td>20</td>
<td>367</td>
<td>27</td>
<td>14</td>
<td>182</td>
<td>F</td>
</tr>
<tr>
<td>1.0</td>
<td>20</td>
<td>408</td>
<td>16</td>
<td>14</td>
<td>152</td>
<td>F</td>
</tr>
<tr>
<td>0.1</td>
<td>30</td>
<td>370</td>
<td>22</td>
<td>12</td>
<td>186</td>
<td>F</td>
</tr>
<tr>
<td>0.5</td>
<td>30</td>
<td>431</td>
<td>11</td>
<td>16</td>
<td>132</td>
<td>T</td>
</tr>
<tr>
<td>1.0</td>
<td>30</td>
<td>459</td>
<td>16</td>
<td>17</td>
<td>98</td>
<td>F</td>
</tr>
<tr>
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<td>411</td>
<td>18</td>
<td>15</td>
<td>146</td>
<td>F</td>
</tr>
<tr>
<td>0.5</td>
<td>40</td>
<td>470</td>
<td>19</td>
<td>13</td>
<td>88</td>
<td>F</td>
</tr>
<tr>
<td>1.0</td>
<td>40</td>
<td>494</td>
<td>11</td>
<td>16</td>
<td>69</td>
<td>T</td>
</tr>
</tbody>
</table>

T indicates that cnfp is greater than cpfn, which means more convective days occur due to urbanization, on the contrary; F indicates less convective days occur due to urbanization.
Figure 1: In 2005, Phoenix and Tucson are represented as the red and blue crossed region. The Phoenix-Tucson Corridor in 2050 is represented as the black slash area. Domain 1 and 2 are represented as the black dash and red box. Elevations are shown in meter.
Figure 2: On the left, 10-year July and August mean temperature (in °C) from a) WRF, c) PRISM, e) NARR data. On the right, 10-year summertime (July and August) mean accumulated precipitation from b) WRF simulated, d) PRISM, f) NARR data.
Figure 3: Domain averaged July and August accumulated precipitation variation in WRF, PRISM and NARR from 1991 to 2000 (upper). Domain averaged July and August domain average temperature variation in WRF, PRISM, and NARR from 1991 and 2000 (bottom).
Figure 4: July and August simulated temperature difference between LULC_2050 and LULC_2005, a) mean temperature in LULC_2005, b) mean temperature difference between LULC_2050 and LULC_2005, c) student t test for mean temperature difference, orange (blue) indicates significant increase (decrease), d), e) and f) are similar to a), b)
and c) except for maximum temperature, g), h) and 1) are similar to a), b) and c) except for minimum temperature.
Figure 5: On the upper, energy diurnal cycle over the newly urbanized area, including sensible heat flux (SH), latent heat flux (LH), ground heat flux (GRD) and net radiation (Net) for LULC_2005 (solid line) and LULC_2050 (dash line). On the bottom, temperature diurnal cycle over newly urbanized area for LULC_2005 (solid line) and LULC_2050 (dash line).
Figure 6: a) Average July and August accumulated precipitation from 1991 to 2000 in LULC_2005. b) July and August precipitation difference between LULC_2050 and LULC_2005 from 1991 to 2000, normalized by number of days. c) Bootstrap test of difference in daily precipitation between LULC_2005 and LULC_2050, blue (orange) indicates statistically significant decrease (increase), d) Similar to c) except for student t test, blue indicates statistically significant decrease.
Figure 7: Diurnal cycle of precipitation over the newly urbanized area in LULC_2050 (red) and LULC_2005 (blue).
Figure 8: Precipitation difference between LULC_2050 and LULC_2005 under each of the flow regime.
Figure 9: Diurnal cycle of Air Conditioning (AC) consumption and temperature at Phoenix metropolitan and Tucson metropolitan.
Figure 10: Scatter plot of the AC consumption and temperature data, the green line indicates the fitted polynomial function.
Figure 11: AC consumption of Tucson and Phoenix in 2005 and 2050, considering both areal enlargement and warmer temperature.
Appendix B: Impact of Irrigation over the California Central Valley on Regional Climate

1 Introduction

1.1 Background

Humans are modifying climate from the regional to the global scale by changing the composition of the atmosphere and by land use/land cover changes (LULCC). Here, we focus on the effects of LULCC on climate, with specific attention to the impacts of agricultural irrigation. Water consumption by irrigation is known to account for about 2% of annual precipitation over land (Sacks et al. 2008) which, although relatively small when averaged over land, is large when considering only irrigated areas. Importantly, while irrigated cropland accounts for only 18% of the world’s cropland or 2% of the total land (Siebert et al. 2005); about 40% of the world’s food is produced in such areas, and about 70% of global freshwater withdrawals and 90% of consumptive water uses are used for irrigation (Siebert et al. 2013).

Irrigation can modify climate mainly by changing the partitioning of available energy, increasing the latent heat flux and decreasing sensible heat flux, when compared to non-irrigated regions. This repartitioning of available energy is more pronounced during the daytime, and the corresponding cooling of daytime surface temperatures (associated with reduced sensible heat flux) has been reported in several studies, using
both observations and modeling (Bonfils and Lobell 2007; Han and Yang 2013; Qian et al. 2013; Marcella and Eltahir 2014).

Modeling studies have reported different magnitudes of irrigation cooling effects, depending on the irrigation schemes prescribed in their models (Qian et al. 2013; Ozdogan et al. 2010; Sacks et al. 2008; Sorooshian et al. 2011; Lo and Famiglietti 2013; Adegbe et al. 2010; de Rosnay et al. 2003; Haddeland et al. 2006; Kanamaru and Kanamitsu 2008; Yang et al. 2016). Most of these studies were performed at the regional scale. For example, Ozdogan et al. (2010) used the off-line un-coupled Noah land surface model to simulate the irrigation impact over the continental US and showed that the energy fluxes and water budget over the irrigated area were significantly improved. At specific locations, inclusion of irrigation also greatly improved the simulated diurnal energy cycles when compared to AmeriFLUX observations. Qian et al. (2013) used the Weather Research and Forecasting (WRF) regional climate model to investigate impacts of irrigation over the southern Great Plains (SGP) region. They incorporated an irrigation scheme into the Noah land surface model following Ozdogan et al. (2010), and found that sensible heat flux decreases (latent heat flux increases) leading to surface cooling of 0.3 - 0.5 °C and increased surface air specific humidity of 0.3 - 0.6 g kg⁻¹. In a relatively new approach, Marcella and Eltahir (2014) coupled the Integrated Biosphere Simulator (IBIS) dynamic vegetation model with a regional climate model, and added a new irrigated cropland biome in which the only plant functional type (PFT) allowed to grow is crop. They found temperature decreases to be as large as 5 °C in the irrigated area, and an accompanying downstream cooling. Using the variable-resolution Community Earth System Model (VR-CESM), Huang and Ullrich (2016) found that irrigation over the
California Central Valley cools the daily maximum near-surface temperature by 1.1 °C. At the global scale, Sacks et al. (2008) investigated irrigation impacts using the Community Atmospheric Model coupled with the Community Land Model. They found that irrigation cools the northern mid-latitudes by about 0.5 °C over the year but warms northern Canada by increasing the annual temperature by 1 °C. The cooling impact is dominated by indirect effects such as increased cloud cover, rather than direct evaporative cooling.

While a consensus emerges from these different studies with regards to daytime surface cooling, the effects of irrigation on nighttime temperatures is not as clear (Kanamaru and Kanamitsu 2008; Bonfils and Lobell 2007; Han and Yang 2013). Similarly, studies have reported different findings regarding the effects of irrigation effects on precipitation. Marcella and Eltahir (2014) reported decreased precipitation over the irrigated area due to the cooling effect and collapse of the boundary layer (i.e., the lower atmosphere is too cool for the PBL to grow enough to trigger convection). In contrast, other studies have reported precipitation enhancement due to irrigation (Lo and Famiglietti 2013; DeAngelis et al. 2010; Qian et al. 2013). For instance, Lo and Famiglietti (2013) used the Community Atmosphere Model coupled with the Community Land surface model to show that irrigation in the California Central Valley (hereafter, CCV) can cause increased downwind summer precipitation of approximately 15% in the Colorado River Basin (hereafter, CRB) leading to ~30% increased streamflow in the Colorado River. DeAngelis et al. (2010) found that the increased precipitation over and downwind of the Ogallala aquifer is consistent with the history of Ogallala irrigation, and used a vapor tracking approach to demonstrate that ET over Ogallala Aquifer contributes
to downwind precipitation. However, Qian et al. (2013) did not find a consistent precipitation signal over the southern Great Plains.

The focus of our work is similar to that of Lo and Famiglietti (2013) and Sorooshian et al. (2011) in that we study the impacts of CCV irrigation on regional hydroclimate. However, there are several important differences, beginning with the different irrigation schemes. In Sorooshian et al. (2011) irrigation starts when solar radiation is less than 50 Wm\(^{-2}\) whereas in Lo and Famiglietti’s work, irrigation is prescribed as water added to irrigated area by fixed amount of ~350mm/year with 40% coming from groundwater and 60% from surface water. Second, in addition to analyzing surface variables as in Sorooshian et al. (2011), we also assess the impacts of irrigation on regional circulation and precipitation. Note that we are using a regional climate model WRF for a total of 6 years of simulations whereas Lo and Famiglietti use the Community Atmosphere Model (CAM) which is a global climate model with ~140 km grid spacing and simulates for a total of 90 years. Finally, the use of a water vapor tracer analysis tool to explicitly quantify both the direct and indirect impacts of irrigation on regional precipitation within WRF is an important part of our analysis.

1.2 Objectives and Scope

As suggested by Sorooshian et al. (2011), a realistic irrigation scheme can be expected to improve the ability of a model to simulate the state variables associated with the impacts of irrigation on regional climate. Therefore, the first objective of this work is to investigate whether or not model performance can be improved by inclusion of a realistic irrigation scheme. We do this by implementing an explicit representation of
irrigation into the WRF model and by ensuring that an appropriate amount of water is used for irrigation.

Our second objective is to investigate the impact of CCV irrigation on local and regional climate, and our third objective is to distinguish between the direct and indirect impacts of such irrigation on local and regional climate. To do this, we use a water vapor transport scheme in the WRF model to track the evapotranspirated water that arises from the irrigated source region (Miguez-Macho et al. 2013; Dominguez et al. 2016); the scheme tags the water vapor produced in the CCV region and tracks its movements in space and time. Depending on the physical processes experienced during the integration time period, water from the source region can be in the form of water vapor, cloud water, ice remaining in the atmosphere, or as precipitation, graupel, or snow falling on the ground. The use of a tracer scheme enables us to differentiate between the direct and indirect impacts of a source region on local and regional climate. For example, if irrigation has induced precipitation enhancement in certain location and is mainly due to moisture transport from the source region (e.g., the CCV), then this region is under the direct impact of irrigation over the source region. On the other hand, if irrigation has led to precipitation increase over a certain location without direct moisture contribution from the source region (e.g., by changing the atmospheric thermodynamics), then this location is under the indirect impact of irrigation in the source region.

This paper is organized as follows: the domain setup and experimental design, observational datasets, details of regional climate model (including the irrigation scheme and the modified KF scheme), and water vapor transport scheme are described in section 2. Section 3 presents the model evaluation against the observations and details of the
irrigation impact on climate variables. Conclusions and discussions are provided in section 4.

2 Experiment Design, Data, and Schemes

2.1 Experimental Design and Model Setup

In this work we apply the Advanced WRF version 3.4.1 (Skamarock et al. 2012) to a research domain that covers the Southwest United States, with irrigation applied only over the CCV (Figure 1). The domain is located within 29.5–49.5° N and 131–99° W over the east Pacific and west United States, with a horizontal grid spacing of 20 km and 27 sigma levels from the surface to 100 hPa. WRF model outputs are generated and saved at 3 hourly time intervals.

The physical parameterizations used in this WRF simulations are: the Noah land surface model (Chen and Dudhia 2001), WSM 6-class microphysics scheme (Hong and Lim 2006), the RRTM radiative transfer model for longwave and shortwave (Mlawer et al. 1997), YSU boundary layer parameterization (Hong and Pan 1996), the Kain-Fritsch convection scheme (Kain and Fritsch 1990). These parameterizations are chosen primarily due to the use of the water vapor tracers (see below). The WRF model simulations include 1) the control simulation (CNTL) with the default Noah land surface model (LSM) without considering the irrigation and 2) the irrigation simulation (IRR) with an explicit representation of irrigation over the CCV. Numerical water vapor tracers are used in all simulations. For each model setup, three dry years (i.e., 2002, 2007, 2013) and three wet years (i.e., 2005, 2006, 2010) are selected based on antecedent precipitation from January to May in California, in order to account for different initial soil moisture conditions. Since precipitation during the JJA over the CCV is very little (almost none)
and hence makes it difficult to determine relative wet and dry years with it. On the other hand, accumulated precipitation from January to May determines the soil moisture condition at the beginning June when irrigation demands start to grow and our irrigation triggering algorithm is highly dependent on the soil moisture conditions. Thus, we define the relative wet and dry years based on the accumulated precipitation from January to May. The dry and wet years include both types of extreme precipitation conditions and thus should cover a representative spectrum of conditions the model may encounter.

For each year, the model is initiated at three different dates from: 1) 1st April, 2) 10th April, and 3) 15th April to 31st October and we focus on the peak of the irrigation season (June-August) during which irrigation exerts the most significant impact. While previous studies have suggested that a 1-month spin-up time is sufficient for such simulations (Liang et al. 2010; Li et al. 2009), for each ensemble member in this study we have used at least a 45-day spin-up period. The North American Regional Reanalysis (NARR) data are used as lateral boundary forcing (Mesinger et al. 2006). Note that surface temperature in NARR is not assimilated and shows strong warm bias in NARR when compared to observation-based gridded dataset (Yang et al. 2015; Huang et al. 2016; Loikith et al. 2015), however, the warm bias is significantly reduced by the WRF model as shown later.

Water vapor tracers embedded into the WRF model Version 3.4.1 allow us to trace moisture that evaporates from any pre-defined source (Miguez-Macho et al. 2013; Dominguez et al. 2016). We use water vapor tracers in all of the simulations. It is important to point out that water vapor tracers are currently only available for the YSU boundary layer scheme, WSM 6-class microphysics, Noah LSM and Kain-Fritsch
convective parameterization (although tracers can also be used at the convective-resolving scale). The tracer scheme, as applied to the cloud microphysics, assumes the atmosphere is well mixed within each grid and vertical level within the clouds.

2.2 Observational Data

The California Irrigation Management Information System (CIMIS) dataset is used in this study to evaluate model performance against an observational dataset. The CIMIS has a network of over 145 automated weather stations in California and was designed to assist irrigators in managing their water resources more efficiently. Each CIMIS station collects meteorological variables, including surface temperature, radiation, humidity, winds, surface pressure and soil temperature on a minute-by-minute basis. Hourly data reflects the previous hour’s 60 minutes of readings. The farmers will estimate the amount and timing of irrigation based on the reference evapotranspiration, crop coefficient, crop type, season (Hanson et al. 1999). The CIMIS data is considered to be of high quality (Sorooshian et al. 2011). In addition to the CIMIS data, PRISM data at 4 km resolution are used to evaluate the spatial pattern and magnitude of temperature and precipitation (PRISM Climate Group, available online at http://prism.oregon.edu).

2.3 Irrigation Scheme

To simulate the effects of irrigation, an irrigation scheme has been coupled to the land surface model in WRF. This irrigation scheme has been implemented in several previous studies (Ozdogan et al. 2010; Qian et al. 2013). Note that Ozdogan et al. (2010) proposed three key questions that an irrigation scheme must resolve: 1) where to irrigate, 2) when to irrigate, and 3) how much to irrigate. Therefore, the mechanism used for irrigation can be described as follows:
1) Where to irrigate

The irrigation fraction map was obtained from the Food and Agriculture Organization of the United Nations (Siebert et al. 2013). The irrigation map layer was developed to compute the fraction of irrigation at 5 arc minute resolution based on subnational irrigation statistics with geospatial information regarding the location and extent of irrigation. We compared the spatial pattern of the irrigation map to the MODIS and USGS data within the WRF model, and found that the USGS dataset has a more consistent spatial pattern compared to the irrigation fraction map. Accordingly, the USGS land use and land cover data was applied in this study; the spatial pattern of areas equipped for irrigation in the CCV is shown in the enclosed red area in Figure 1.

2) When to irrigate

Irrigation is triggered only when irrigation fraction is greater than zero and the greenness fraction in the Noah land model is above a certain threshold given by:

\[
GF_{\text{threshold}} = GF_{\text{min}} + 0.40 \times (GF_{\text{max}} - GF_{\text{min}})
\]

Eq. 1

where \(GF_{\text{max}}\) and \(GF_{\text{min}}\) are the annual maximum and minimum greenness fraction at a grid cell and \(GF_{\text{threshold}}\) is the threshold set to determine whether the grid cell is in the growing season.

When the threshold of greenness fraction is met, the irrigation scheme examines the antecedent soil moisture condition, and a quantity named soil moisture availability (MA, see Eq. 2 below) is defined to determine the root-zone soil moisture availability (as in Ozdogan et al. (2010) and Qian et al. (2013)). At 0600 Local Time (LT) the model examines the soil moisture condition, and triggers the irrigation scheme only when MA is below the specific threshold. Once triggered, irrigation water is added at a uniform rate
during 0600 LT to 1000 LT, until soil moisture reaches the field capacity (defined as maximum amount of water that the unsaturated zone of a soil can hold against the pull of gravity) at which point irrigation is stopped.

$$MA = \frac{SW - SW_{wp}}{SW_{fc} - SW_{wp}}$$  \hspace{1cm} \text{Eq. 2}

3) How much to irrigate

Lo and Famiglietti (2013) suggested an annual mean irrigation amount of ~350 mm in the California Central Valley. Over the same region, Sorooshian et al. (2011) applied irrigation from June to August with a monthly average irrigation amount of about 107.5 mm for the entire irrigation region. We use estimate of Sorooshian et al. (2011) because it matches observations. In our scheme, the water amount required for irrigation is determined by the difference between the current soil moisture content and field capacity at the trigger time, i.e. when MA is below the specified threshold. Qian et al. (2013) used 50% as the threshold for MA; however we found that this value leads to an overestimation of irrigation over the region compared to that of Sorooshian et al. (2011) and Hanson et al. (1999). Accordingly, we calibrated the irrigation scheme so that the average monthly irrigation amount remains close to the benchmarks, and found irrigation amount to be very sensitive to the choice of the threshold for MA; the best value for the threshold as found to be 43%, which leads to realistic average monthly irrigation amount of 106.5 mm.
2.4 Modified KF scheme

Parameterizations are used in the climate models to represent the unresolved subgrid scale physical processes and estimate the exchanges of mass, energy and momentum (Kain and Fritsch 1990; Bechtold et al. 2001; Yang et al. 2012). However, physical parameterizations may introduce uncertainties in that they generally use conceptual or empirical relationships to approximate the subgrid scale processes (Yan et al. 2014). Additionally, due to the non-linearity of interactions among physical processes, large uncertainties may exist when parameterizations are applied in models. Consequently, it is necessary to tune the parameters within the parameterization schemes to ensure the proper representation of the physical process on the grid scale. In this study, a finely tuned convective parameterization scheme (i.e., the Kain-Fristch scheme) was utilized following Yang et al. (2012) and Yan et al. (2014).

The KF convective parameterization is a 1-dimensional mass flux cloud model (Kain and Fritsch 1993; Kain 2004; Kain and Fritsch 1990). The scheme starts by identifying potential source layers for convective clouds, i.e., the updraft source layer (USL) of a depth of at least 60 hPa. Convection is only possible when the USL has positive buoyancy and ascends. Deep convection is activated when vertical velocity remains positive over a depth that exceeds a specified minimum cloud depth. Otherwise, the base layer of the USL moves up one model layer and the procedure is repeated until the search reaches the lowest 300 hPa of the atmosphere and terminates. Then convective updrafts, including entrainment and detrainment processes, and downdrafts are represented using a steady-state entraining-detraining plume model. Air mass is exchanged between the updraft and the environment by entrainment and detrainment. The
rate of the entrainment mass flux rate is inversely proportional to the cloud radius as given in Kain and Fritsch (1990). The detrainment occurs by assuming the fractional amount of environment mass in the transition zone exceeds certain neutrally buoyant mixture threshold. The downdraft is fueled by evaporation of condensate that is generated within the updraft and moves downward in a Lagrangian sense. The downdraft is terminated if it becomes warmer than its environment or if it reaches the ground (Kain 2004).

Previous studies have shown significant improvement in model precipitation by calibrating the convection scheme (i.e., KF scheme) in the model (Yang et al. 2012; Yan et al. 2014). As shown in Yang et al., (2012), the default KF scheme overestimates the frequency of precipitation across all rain rates especially for heavy rains, whereas the calibrated KF scheme produce much more realistic rain rate both in terms of magnitude and spatial pattern when compared to observations. Using the same approach, Yan et al. (2014) found that the optimized KF scheme not only reduces the overestimation of the precipitation, but it improves the representation of latent heat flux and net shortwave radiation as well. Here we follow the approach presented in Yang et al. (2012) and calibrate the critical parameters of the scheme. Brief descriptions and default values of the parameters are listed in Table 1. More details of the impact of the parameters on model precipitation can be found in Yang et al. (2012).

3 Results

3.1 Model Evaluation

To ensure that the WRF model is correctly simulating precipitation, we examined the convective parameterization scheme (i.e., KF scheme) in the model. Model
simulations with: a) the default KF scheme, b) KF scheme with the parameter set as suggested in Yang et al. (2012), and c) our own calibrated KF schemes, were examined to ensure adequate model performance in simulating precipitation. Figure 2 shows the precipitation pattern for July 2006. The default KF scheme clearly overestimates precipitation – a common issue with the KF scheme (2012). Using the KF parameters suggested by Yang et al. (2012), however, the model underestimates precipitation with a precipitation band over the southeast of the domain missing and overestimates precipitation over Utah. Thus, additional calibration of the KF scheme was required to alleviate these issues. The wet bias in domain average monthly precipitation within the red box decreased from +11.0 mm for the default KF scheme, to +7.8 mm for the suggested KF scheme and +6.5 mm for the calibrated scheme. Similarly, for the blue box (roughly, the CRB), domain average monthly precipitation bias was +69.9 mm, +32.0 mm and +32.5 mm for the default, suggested and calibrated KF scheme respectively. The underestimation of precipitation band over New Mexico was also reduced when using our calibrated scheme. Overall, the overestimation of precipitation in the domain was significantly reduced by calibration of the KF scheme.

The spatial pattern of surface air temperature at 2m for July 2006 is shown in Figure 2 using the PRISM data. All of model simulations produced a warm bias compared to PRISM, with +0.20, +0.06 and +0.10 °C for the default, suggested, and the calibrated KF schemes over the entire domain. Note that the warm bias in the NARR is +0.8 °C compare to PRISM, WRF model is able to significantly reduce the bias in the forcing NARR data. Overall, the warm bias in the domain was reduced with calibration. It is somewhat counter-intuitive that the wetter default KF scheme produced warmer
surface temperatures, particularly in the blue box (CRB) region where warm bias was +2.2, +1.5 and +1.5 °C for the default, suggested and calibrated KF schemes. Figure 2 shows that, compared with the default KF scheme, the calibrated scheme reduced the probability of convective rainfall and thus the wet bias. As a result, the vertical structure of clouds (Figure S.1) and the net radiation at the surface (Table S.1) was changed, as discussed in the Supplementary Material.

3.2 Irrigation Impact

To ensure the amount of irrigated water applied to the CCV is realistic when compared to the benchmark values, the threshold of moisture availability was calibrated, it being the most sensitive parameter in controlling irrigation water amount.

We focused on the results of June, July and August (JJA) since irrigation peaks during this period. Figure 3 compares the simulated diurnal cycle of 2 m mean air temperature, relative humidity, and dew point temperature over CCV with the observational CIMIS data. The additional water introduced by the irrigation scheme reduces the warm bias by ~0.7 °C from +2.62 °C in the CNTL simulation to +1.94 °C in the IRR simulation. There is a clear difference between the IRR and CNTL simulation in the 2m air temperature during the daytime (0700 – 1900 LT) and the difference gradually diminishes at night.

It is apparent that the CIMIS surface air temperature is lower than both IRR and CNTL simulations during the daytime. This can be explained by the fact that the CIMIS observations were measured under saturated conditions, while the model crops are not in saturated soil moisture conditions. Indeed, as shown in Sorooshian et al. (2011), temperature is much closer to the CIMIS observational data when a high value for the
soil moisture allowable depletion parameter is applied. It is not clear why CIMIS temperature is warmer than IRR simulation during 1700-2100 LT, though similar result has been reported in Sorooshian et al. (2011). Dew point temperature shows very similar diurnal variation pattern to the CIMIS data with irrigation scheme, as the mean absolute bias reduces from 3.2 °C in the CNTL simulation to 0.7 °C in the IRR simulation. Similarly, relative humidity is also improved in the IRR simulations with mean absolute bias of 13.3% without irrigation to 7.7% with the irrigation scheme. During daytime from 0700-1900 LT, mean absolute bias is reduced by 1.6 °C, 3.6 °C and 8.8% for surface temperature, dew point and relative humidity in the IRR simulation. The effect of irrigation scheme is less significant during the night (1900-0700 LT), with bias slightly reduced by 1.3 °C and 2.4% for dew point temperature and relative humidity, bias in surface temperature slightly increases by 0.2 °C. With the representation of irrigation, the diurnal variation of surface temperature, dew point and relative humidity show greater improvements during the daytime than during the nighttime. This has to do with the timing of irrigation, which is from 6am to 10am (LT). Irrigation-induced additional water evaporates mainly during the day and changes the energy partitioning. Because evapotranspiration is very limited at night, the IRR and CNTL simulations are similar during the nighttime.

Table 2 provides statistical results of averaged surface variables from observational CIMIS data and model results with, and without, the irrigation scheme. There are 9 stations that the model categorized as irrigation grids, very close to 8 stations when the resolution is 36 km as indicated in Sorooshian et al. (2011). Model results are biased in the control runs but when irrigation is included into the model, results are improved in
regards to surface temperature (T2), dew point temperature (TD2), relative humidity (RH2) and first layer soil temperature (TSLB) in both wet and dry years. While improvement in the surface temperature due to the irrigation scheme seems to be minor, with bias and RMSE decrease by 39%, 32%. Improvement in moisture related variables increase significantly, biases are reduced by 72% and 56% and RMSE by 50% and 38% in TD2 and RH2. Because of better representation of the soil moisture field, bias and RMSE in TSLB are reduced by 64% and 42% respectively.

In summary, the comparison with the CIMIS data shows that the additional water added by the irrigation scheme results in cooler and wetter conditions over the CCV. The detailed comparison of our model simulations with CIMIS data shows that surface variables, such as surface air temperature, dew point temperature, and relative humidity, as well as soil temperature are improved by introduction of a realistic irrigation scheme.

Next, changes in other climatic variables caused by the irrigation scheme are examined to determine the impact of the irrigation scheme on local and regional climate. Results are averaged over all years and initial condition ensemble members and presented as the difference between the irrigated (IRR) and non-irrigated (CNTL) simulations.

The top panels of Figure 4 show the spatial pattern of difference in sensible heat flux (SH), latent heat flux (LH), surface air temperature (T2) and specific humidity (Q2) between the IRR and CNTL simulations. Irrigation increases evapotranspiration (ET) over this region. The additional water changes the surface energy partitioning, leading to more LH and less SH. Averaging over the irrigated grids, LH is almost doubled and increases by 32.10 W m\(^{-2}\) while sensible heat flux decreases by 23.80 W m\(^{-2}\) (22.4%) over the same region. Meanwhile specific humidity increases by about 10% with 0.68 g
kg\(^{-1}\) more water vapor over the CCV and a relatively smaller amount of increase is also shown downwind. Due to the decrease in SH, T2 is decreased by 0.39 °C. Changes in these surface variables have mainly a local effect and do not extend into other regions.

The planetary boundary layer (PBL) strongly affects the exchange of mass, momentum and energy between the surface and the atmosphere. The PBL is directly influenced by the Earth’s surface, and its depth is a reflection of surface roughness, wind speed and surface fluxes. Lifting condensation level (LCL) is the level at which an air parcel becomes saturated when lifted adiabatically from the surface. It is strongly related to the PBL structure and affected by the partitioning of available energy at the surface. Generally, the height of LCL and the time of convection initiation are related to the boundary layer structure (Berg and Kassianov 2010). Moist convection is likely to initiate when the PBL depth crosses the LCL (the so-called LCL crossing) (Ek and Mahrt 1994; Ek and Holtslag 2004; Juang et al. 2007). In our simulations, irrigation-induced decrease in PBL depth over the CCV is 103.16 m while decrease in LCL depth is 179.2 m, indicating a higher probability of LCL crossing in the irrigation simulations (Figure 4).

Meanwhile, the level of free convection (LFC) decreases by 526.78 m over the CCV and its downwind region, making it easier for convection to develop. Both higher probability of LCL crossing and decreasing in LFC increase the chances of precipitation. However, LCL crossing is a necessary but not sufficient condition for the initiation of deep convection (Yin et al. 2015; Juang et al. 2007). Convective available potential energy (CAPE) should also be considered at the time of LCL crossing in order for moist convection to occur. CAPE typically must exceed 400 J kg\(^{-1}\) to trigger convective rainfall in the mid-latitude continental regions (Battan 1973; Findell and Eltahir 2003).
Particularly, irrigation has induced an area-averaged increase in CAPE of about 58.89 J kg⁻¹ (~20%, see Figure 4). The increase in CAPE along with LCL-crossing suggests that it is more likely to form precipitation in the IRR simulation over the CCV. However, as shown later there is no significant change in precipitation over the CCV. Climatologically, precipitation over the CCV is at a minimum during the summer so local changes are negligible.

The amount of moisture within the PBL and surface heating are key regulators in cloud formation and involved in critical processes through which land and atmosphere interact (Qian et al., 2013). Changes induced by irrigation and associated changes in the land-atmosphere feedback can have an impact on the thermodynamic structure of the PBL. To investigate the irrigation impact on the vertical structure of several key thermodynamic variables, profiles of these variables over the CCV have been created at 1300 LT during the day and 0100 LT at night (Figure 5).

During the daytime, nearly constant potential temperature and specific humidity should be expected within the PBL due to turbulent mixing. Such pattern is clear for control simulations at 1300 LT in Figure 5. As for the irrigation simulations, since the timing is only 3 hours after irrigation ended, vertical mixing is likely not able to bring surface moisture to the upper PBL in a short time. Moist static energy (MSE) is an important indicator for moist static instability, and a higher MSE is likely to increase convective instability and thereby increase the probability of precipitation (Eltahir 1998). Domain averaged MSE in the PBL is clearly increased due to irrigation during the day. Relative humidity is also increased throughout the PBL.
Similar profiles for the nighttime at 0100 LT are shown in Figure 5. During the nighttime, the PBL is stable due to radiative cooling, as evident in the potential temperature profile. Potential temperature is almost the same for the IRR and CNTL simulation, because evapotranspiration is weak at night. The difference in specific humidity is much smaller than during the day and mainly exists in the lower levels. There is, however, a clear difference in MSE and RH between the irrigation and control simulations, particularly in the middle levels between 1000 m and 3000 m, where the residual layer is present. The vertical profile of RH difference between IRR and CNTL simulations from 1300 to 0100 LT is shown in Figure S.2. It shows that there exists a large RH difference at lower levels at 1300 LT, and the additional moisture in the IRR simulations is gradually transported to higher levels with the growth of PBL at 1600 LT. After sunset, the PBL starts to shrink, the additional moisture remains in the residual layer and leads to the difference in the RH vertical profile. The difference in MSE is directly related to the difference in the moisture in the mid-levels.

3.3 Water Vapor Transport: How irrigation in CA affects precipitation downwind.

Figure 6 shows the difference in Integrated Water Vapor (IWV) between the IRR and CNTL simulations. Overall, IWV is clearly increased over the CCV and slightly increased over the downwind region, indicating that the irrigation scheme has significantly increased atmospheric moisture, as expected. We also plot the IWV that originates from the tracers of irrigated water (IWVT). As expected, the results show similar spatial patterns and magnitudes, indicating that changes in the IWV are mostly due to the additional water input by the irrigation scheme.
To understand the difference in spatial patterns shown in Figure 6, we analyze the moisture transport. Figure 7 shows the water vapor mixing ratio difference along with average wind patterns at different model levels from 800 hPa to 500 hPa. Moisture mainly exists from the surface to about 600 hPa. Moisture differences mainly occur in the lower atmosphere and diminish gradually with increasing height. Differences in water vapor between the IRR and CNTL simulations are almost negligible around the 600 hPa level.

The wind field is affected by the North Pacific High pressure to the west and the Bermuda high to the southeast of the domain. This is evident from the wind pattern in Figure 7. Near the surface over the Pacific Ocean, wind is typically northerly in the northwest due to the Pacific High and becomes north-northwesterly in the southwest. Over land, wind directions are complicated by the terrain effect. Wind is typically affected by the Bermuda high and becomes south-southwesterly over the California and Arizona, which brings the extra moisture northeastward from the CCV to its downwind region, e.g., Nevada, Utah. Such pattern is well reflected in the water vapor differences (shaded) in the lower levels, leading to a positive anomaly in water vapor in Nevada, Utah, and southern Idaho.

3.4 Quantitative Analysis of Water Vapor Flux over the CCV

In order to estimate water vapor transport over the CCV, zonal and meridional fluxes are analyzed. A simplified approximation of the CCV region is shown in Figure 8. Zonal flux moves into the CCV through sides 1 & 2 (influx), and out through sides 4 & 5 (outflux). Similarly, meridional flux moves in through sides 2 & 3 (influx), and out through sides 5 & 6 (outflux).”
By considering irrigation over the CCV, the model has led to increased atmospheric moisture, as shown earlier. Zonal influx slightly decreases from \((7.93 \pm 1.45) \times 10^{13} \text{ kg month}^{-1}\) to \((7.89 \pm 1.45) \times 10^{13} \text{ kg month}^{-1}\) while zonal outflux increases from \((5.50 \pm 1.12) \times 10^{13} \text{ kg month}^{-1}\) to \((5.74 \pm 1.17) \times 10^{13} \text{ kg month}^{-1}\), leading to net zonal flux decreases from \((2.43 \pm 0.80) \times 10^{13} \text{ kg month}^{-1}\) to \((2.15 \pm 0.82) \times 10^{13} \text{ kg month}^{-1}\). Here, numbers in the parenthesis indicates mean ± 2 times standard deviation. Meridional influx and outflux both decrease. Considering the increased water vapor over the CCV, it implies that irrigation has induced a weaker northerly flow over the CCV. Overall, the meridional net flux does not change much, slightly decreasing from \((-2.57 \pm 0.82) \times 10^{13} \text{ kg month}^{-1}\) to \((-2.50 \pm 0.86) \times 10^{13} \text{ kg month}^{-1}\). The net impact of irrigation on moisture flux mainly reflects in the zonal direction, leading to a weaker influx and stronger outflux, while the net impact in the meridional direction is almost negligible compared to changes in the zonal moisture flux.

A similar analysis is performed on tracer moisture (numbers show in the parenthesis in the bottom panels of Figure 8). It shows that tracer moisture flux has been strengthened in all directions. Particularly in the meridional direction, stronger tracer flux to the north and south indicates that there is a low-level divergence over the CCV, as shown later.

The convergence term is calculated from the moisture budget equation over the CCV (see details in Schmitz and Mullen (1996)) and the results above suggest that irrigation induces stronger divergence over the CCV during the JJA months, as shown in Figure 9. As a result, divergence over the CCV generates outflows to the west and east, weakening the zonal moisture influx while strengthening the zonal outflux from the CCV.
The moist eastward flow has a potential to rise orographically along the Sierra Nevada Range and induce topographic precipitation as displayed in the precipitation difference pattern in Figure 10. Under both dry and wet conditions, a consistent increase in precipitation is present on the windward side of the Sierra Nevada Range (not shown). Over the CCV, the divergence and the stability variables in Section 3.2 act as opposing mechanisms for precipitation, leading to a negligible change in precipitation over the CCV.

3.5 Precipitation and Tracer Precipitation

Figure 10 displays the precipitation and tracer precipitation in CNTL simulations in all years and their changes induced by the irrigation scheme. Typically, during dry years with relatively dry winter and spring, irrigation will have a larger impact on precipitation, compared to wet years (not shown). This is straightforward since during dry years there will be relatively larger atmospheric demand for irrigated water compared to wet years. Once the soil moisture deficit is removed, this additional water tends to evaporate into the atmosphere. The entire domain average precipitation increases by 3.48% due to irrigation, from 0.86 mm/day to 0.89 mm/day. Precipitation difference in Figure 10 suggests a consistent increase in precipitation over the CRB, with average precipitation increases by about 2.9% from 1.48 mm/day to 1.52 mm/day. This increase is also found to be robust, varying from 0.64% to 4.8% among the 18 ensemble members (6 years, each year with three different initial conditions).

Further investigation of the tracer precipitation from the CNTL simulations indicates that water vapor that evaporates from the CCV region tends to move northeastward and precipitate mainly in the state of Oregon and northeast Idaho,
following the climatological wind direction (Figure 7). After irrigation is implemented, more water vapor evaporates from the CCV and is able to precipitate in Nevada, Idaho and certain parts of Utah and Colorado. While the increase in tracer precipitation occurs in both wet and dry years over the CRB, the pattern of tracer precipitation increase is confined to northern CRB and thus cannot fully explain the precipitation changes in Figure 10, where precipitation increase is also seen over Arizona along the Mogollon Rim and part of New Mexico. These results indicate that the precipitation change over the CRB may be not only under the direct impact of additional moisture in the atmosphere due to irrigation, but also due to indirect impacts. Such a finding is also consistent with Lo and Famiglietti (2013), even though they suggested a much higher percentage of 15% in precipitation increase over the CRB. The ratio of tracer precipitation to total precipitation in Figure S.3 is consistent with the water vapor mixing ratio difference and the average wind pattern shown in Figure 7, with magnitude usually less than 5% except for regions close to CCV.

To explain the possible mechanism by which the IRR scheme produces more precipitation over the domain, we focus mainly on two sub-domains as delineated in Figure 2. The CNR is directly influenced by the additional moisture from irrigation over the CCV (Figures 7 & 10). However, over the CRB the mechanism is likely different, considering precipitation increase over the southern CRB in Arizona and New Mexico where direct moisture contribution from the CCV has not been detected (Figures 6, 7 and 10).

We look at the precipitation difference over the CNR between the IRR and CNTL simulations by aggregating the 3-hourly precipitation difference into daily precipitation
and calculating the running mean of 5-day precipitation difference. As shown in Figure 11, the distribution of precipitation difference skews towards the positive side, indicating an increase in precipitation in this region, which is in accordance with Figure 10. Then we define a precipitation difference threshold, corresponding to the 75\textsuperscript{th} percentile of precipitation difference for this region, which equals to +0.71 mm 5day\textsuperscript{-1}. Then we plot the composite of 500 hPa geopotential height difference for all pentads that have precipitation difference (IRR-CNTL) greater than +0.71 mm 5day\textsuperscript{-1}.

Over the CNR, when precipitation difference is above the 75\textsuperscript{th} percentile, 500 hPa geopotential height difference between IRR and CNTL shows a wave pattern, likely associated with the latent heat release at mid-levels (Gall 1976). Gall (1976) had shown that release of latent heat would introduce a mid-level (500 hPa) wave of wavenumber 15 (of wavelength ~2000 km), which is of comparative size to the wave pattern as displayed in Figure 11.

As shown in Figure 10d, CCV irrigation enhances direct precipitation downwind. The geopotential low displayed in Figure 11 is likely associated with mid-level anomalous latent heat release in this downwind region. The geostrophic winds associated with the geopotential height difference pattern, as seen in Figure 11, result in strengthened southerly flow along the eastern border of Utah, and favor inland penetration of moisture from the Gulf of California. The geopotential high formed over the CRB is similar to the so-called “Four-corners High” during the monsoon season, which can draw moisture from the Gulf of California or the core of monsoon region and induce thunderstorm events in the southern CRB. Since precipitation difference over CNR is also highly skewed towards the positive side, such a wave pattern has a high
probability to form, which is then expected to increase precipitation over the CRB as well. Further analysis shows that during days when the control simulation generates precipitation over the CRB, the irrigation simulation enhances precipitation over the region, and the amplification increases at high intensity precipitation events. Notably, the changes are not due to the direct effect of moisture from irrigation but due to enhanced southerly moisture transport.

4 Summary and Discussion

We incorporated an irrigation scheme into the Noah land surface model coupled with the WRF regional climate model, and calibrated the scheme for the agricultural area in the CCV. The convective parameterization scheme (KF scheme) in WRF model was also calibrated to reduce the tendency to overestimate precipitation in the domain, thereby reducing bias in both temperature and precipitation. Despite the calibration, a wet bias in simulated precipitation persists.

We conducted experiments with, and without, the irrigation scheme. Each experiment was run for 3 wet and 3 dry years based on soil moisture condition in the previous winter and spring and using 3 different initial conditions. Air temperature, dew point temperature and relative humidity at 2 m were evaluated against CIMIS station data. The irrigation scheme resulted in improved simulation of the diurnal cycle of surface variables. Mean absolute bias in diurnal cycle were reduced by 0.7 °C, 2.5 °C and 5.5% for temperature, dew point and relative humidity by including the irrigation scheme. The CNTL simulation tends to have drier and warmer lower atmosphere whereas the irrigation scheme reduced the model bias by adding additional water to the soil, thereby changing the partitioning of energy and leading to stronger evapotranspiration (more
latent heat and less sensible heat flux), which lowered air temperature and increased humidity. Comparison of 3-hourly model results from IRR and CNTL simulations with in situ observations suggests that the irrigation scheme is able to reduce model bias by 39%, 72%, 56% and 64% and reduce RMSE by 32%, 50%, 38% and 42% for surface air temperature, dew point temperature, relative humidity and soil temperature respectively. Meanwhile, including the irrigation scheme increases correlations with observation as well, thus providing support for the validity of our irrigation scheme.

The daytime vertical profile suggests that local changes between IRR and CNTL mainly exist in the boundary layer. Simulations with irrigation have lower potential temperature, higher humidity and higher instability in the boundary layer. Due to these changes, CAPE increases and LCL height decreases over the CCV. Despite these changes, differences in precipitation are negligible over the CCV – due to the fact that climatological precipitation in the summer is small over this region. However, analysis of the IRR and CNTL simulations indicates that changes in integrated water vapor occur mainly downwind of the CCV region. Using water vapor tracers, we find that moisture that evaporates from the CCV is advected and precipitates northeast of the CCV. Strong divergence over the CCV lead to strengthened zonal moisture outflux, which generates increased precipitation over the windward side of the Sierra Nevada Range.

While direct evaporation from irrigation contributes to precipitation northwest of the CCV, we also find changes in precipitation in the southwestern US (CRB). Changes in precipitation over the CRB region are a result of indirect effects, not direct moisture advection. The irrigation simulations reveal a synoptic-scale geopotential height pattern at 500 hPa likely associated with the release of latent heat. Anomalous low pressure,
centered on the state of Utah, enhances cyclonic winds at upper levels and promotes moisture transport from the Gulf of California to the CRB region. In a previous study, Lo and Famiglietti (2013) used the Community Atmosphere Model (CAM) to study the CCV irrigation impact on the CRB. They also found changes in CRB precipitation due to indirect mechanisms and suggested that land-atmospheric interactions over the CRB are the critical mechanism for increased precipitation over the CRB, stating that irrigation over the CCV acts as a trigger for enhancing precipitation. In our work we present an alternate, although not mutually exclusive, physical mechanism to explain the indirect effect on CRB precipitation.

There are, however, certain aspects that this study is not able to resolve. Even though we have calibrated the KF scheme, it still tends to overestimate precipitation in the domain, which seems to be associated with structural errors associated with the scheme. Further, a resolution of 20 km is not fine enough to properly consider topographic effects over the CCV; the CCV is a long narrow valley that lies between the Pacific and the Sierra Nevada Range and corresponds to only a few grid cells width in the zonal direction. Potentially the model may be smoothing out the topographic effect and thereby omitting certain important effects that the CCV may have on regional climate. Finally, the model resolution may be too coarse to accurately represent the precipitation mechanisms responsible for summer monsoonal precipitation in the Southwestern US (Tripathi and Dominguez 2013).

**Acknowledgement**
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Reference


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Siebert, S., V. Henrich, and K. Frenken, 2013: Update of the Digital Global Map of Irrigation Areas to Version 5. ...


### Tables

Table 1: Modified KF scheme parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Def./Mod.</th>
<th>Range</th>
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<tr>
<td>Pd</td>
<td>Coefficient related to downdraft mass flux rate</td>
<td>0/0.852</td>
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<tr>
<td>Pe</td>
<td>Coefficient related to entrainment mass flux rate</td>
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<td>Ph</td>
<td>Starting height of downdraft above updraft source layer (USL) (hPa)</td>
<td>150/331</td>
<td>[50, 350]</td>
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<tr>
<td>Pt</td>
<td>Maximum turbulent kinetic energy in sub-cloud layer (m² s⁻²)</td>
<td>5/4.62</td>
<td>[3,12]</td>
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<tr>
<td>Pc</td>
<td>Average consumption time of convective available potential energy (CAPE) (seconds)</td>
<td>2700/3386</td>
<td>[900, 7200]</td>
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Table 2: Bias, root mean squared error (RMSE) and correlation of simulated model results when compared to CIMIS observations for surface air temperature (T2), dew point temperature (TD2), relative humidity (RH2) and first layer soil temperature (TSLB). Model results are extracted from irrigated grids that are closest to the CIMIS stations.

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<tr>
<th>Variables</th>
<th>T2</th>
<th>TD2</th>
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<tr>
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<td>CNTL</td>
<td>IRR</td>
<td>CNTL</td>
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<td>1.70</td>
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<td>CNTL</td>
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<tr>
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<td>2006</td>
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<td>IRR</td>
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<td>0.62</td>
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</table>

*Bold numbers indicate that the absolute bias in the IRR simulation is less than that in the CNTL simulation, statistically significant at p = 0.05 using the two sample t test.
Figures

Figure 1: Model domain, CIMIS stations, and areas equipped with irrigation.
Figure 2: On the left, model simulated July total precipitation spatial pattern for 2006 with a) default KF scheme, b) previously suggested KF scheme, c) our calibrated KF scheme. Observational data are shown in d). The red box encircles California and its nearby region is defined as CNR and the blue box delineates the Colorado River Basin (CRB). On the right, same as the left but for surface air temperature.
Figure 3: Diurnal cycle of 2 m air temperature (T2), dew point temperature (TD2) and relative humidity (RH2) from the CIMIS observations, the CNTL and IRR simulations.
Figure 4: Simulated differences between the IRR and CNTL simulations in a) sensible heat flux (W m$^{-2}$), b) latent heat flux (W m$^{-2}$), c) surface air temperature (°C), d) specific
humidity (g kg$^{-1}$), e) convective available potential energy (CAPE, J kg$^{-1}$), f) PBL height (m), g) lifting condensation level (LCL, m) and h) level of free convection (LFC, m). Stippled areas indicate that differences between IRR and CNTL are statistically significant using the two sample t test at $P = 0.05$. 
Figure 5: Vertical profiles of potential temperature (K), specific humidity (g kg\(^{-1}\)), moist static energy (kJ kg\(^{-1}\)) and relative humidity (%) in the daytime (red) at 1300 LT and night time (blue) at 0100 LT from IRR (dash line) and CNTL (solid line) simulations. Horizontal lines represent the planetary boundary layer height.
Figure 6: a) Integrated water vapor (IWV) difference between the IRR and CNTL simulations, b) integrated water vapor tracer (IWVT) difference between the IRR and CNTL simulations. Stippled areas indicate that differences between IRR and CNTL are statistically significant using the two sample t test at P = 0.05.
Figure 7: Shaded regions indicate the water vapor mixing ratio (g kg$^{-1}$) difference between the IRR and CNTL simulations at different levels ranging from 800 hPa to 500 hPa in a) through d). Vectors indicate the winds at each level.
Figure 8: In the top panel, terrain height in the model domain (shaded). Red enclosed area represents the California Central Valley (CCV) for simplicity. In the bottom panel, averaged JJA vertically integrated moisture flux over the CCV region in the CNTL simulation (left) and IRR simulation (right), units are $10^{11}$ kg month$^{-1}$. Numbers in the parenthesis indicates the same calculation but for water vapor tracer.
Figure 9: (Left) Difference in convergence between IRR and CNTL simulations for JJA months (see details in Schmitz and Mullen (1996), negative values indicate divergence). (Right) A schematic depiction of how divergence over CCV may affect the upwind side of the Sierra Nevada.
Figure 10: a) Simulated average precipitation from all years in CNTL simulations; b) simulated precipitation difference between IRR and CNTL for all years; c) and d) are the same as a) and b) but for tracer precipitation, respectively (mm/day).
Figure 11: On the left, distribution of 5-day precipitation difference (IRR-CNTL) over CNR for all years and all ensemble members. The positive skew indicates that precipitation increase over this region. On the right, 500 hPa geopotential height difference between the IRR and CNTL simulations at pentads when precipitation difference over the CNR (left) is above 75th percentile of its time series. Vectors indicate the wind anomalies at 500 hPa level.
Appendix C: Large and Local Scale Features Associated with Heat Waves in the United States and the Performance of the NARCCAP Ensemble in Simulating Heat Waves

1 Introduction

Heat waves are often associated with detrimental socio-economic impacts on agriculture, energy consumption and human health (Haines et al. 2006; Vanos et al. 2014; Semenza et al. 2009). During the heat wave of July 1995, the city of Chicago reported 700 more deaths than average, most of which are heat-related (Semenza et al. 2009). From 1980-2003, heat wave events have caused economic losses ranging from billions to tens of billions in the US dollars per episode (Kunkel et al. 1999). Furthermore, due to anthropogenic global warming, changes associated with temperature extremes are likely to have an increasing severe impact on society in the future (Seneviratne et al. 2012). Therefore, the physical processes associated with the initiation and maintenance of heat waves in different geographical locations, as well as the severity, frequency and duration of heat waves, are of great relevance to society.

Many recent studies have unveiled the key processes involved in the formation of heat waves, including large scale meteorological patterns (LSMP) (Lau and Nath 2012; 2014; Cassou et al. 2005), key interactions between land and atmosphere (Fischer et al. 2007b,a; Seneviratne et al. 2010; Loikith et al. 2015) and soil moisture impacts (Whan et al. 2015; Hauser et al. 2016; Mueller and Seneviratne 2012; Lorenz et al. 2010). In particular, heat waves are generally associated with large scale anticyclone circulation
patterns (Black et al. 2006; Lau and Nath 2012), which are often characterized by 500-hPa geopotential height anomalies that induce subsidence, clear skies, and warm-air advection at the surface (Xoplaki et al. 2003; Meehl and Tebaldi 2004; Lau and Nath 2012). Surface temperature response to such geopotential height anomalies is amplified by a positive feedback, by which less energy is partitioned into latent heat flux owing to lack of soil moisture and more becomes sensible heat flux and increases surface temperature (Seneviratne et al. 2006; Ferranti and Viterbo 2006). In the mega-heatwave in France 2003 and Russia 2010, Miralles et al. (2014) suggested that extreme temperatures in the mega-heatwaves can be explained by the combined effect of multi-day memory of the soil and the atmospheric boundary layer.

Several studies have shown that soil moisture is linked to temperature extremes through the partitioning of energy (Mueller and Seneviratne 2012; Ford and Quiring 2014; Vautard et al. 2007; Fischer et al. 2007b). Mueller and Seneviratne (2012) showed a strong relationship between the number of hot days and the preceding precipitation deficits. Vautard et al. (2007) used meteorological records of 58 years and showed that hot summers are preceded by winter rainfall deficits over Southern Europe. Given the relative long term memory of soil moisture (compared to the atmosphere), further analyzing the role of soil moisture in heat waves in the US would help with early warning and prediction for extreme heat events.

However, few studies have synergistically considered the role of large scale meteorological patterns and antecedent surface condition in causing heat waves in the US. In this work, the large-scale meteorological conditions and antecedent surface conditions associated with heat waves are investigated to understand the conditions that lead to heat
wave formation for different climate divisions in the US (see Figure 1). The first goal is to understand the physical processes associated with heat wave initiation with a reference dataset, the Modern Era-Retrospective Analysis for Research and Applications (MERRA) reanalysis. Regional climate models are often used to provide the high-resolution results of regional climate projections for decision making. The ability of regional models to accurately represent the physical processes associated with heat waves is of great societal importance if these models are then going to be used for future projections of heat waves at the regional scale. For this reason, in the second part of this study we evaluate the ability of the regional models that participated in the North America Regional Climate Change Assessment Program (NARCCAP) in reproducing the large-scale and local processes associated with heat waves. Section 2 briefly introduces the methodology including the MERRA dataset and NARCCAP models. Section 3 presents the results, followed by discussion and conclusions in Section 4.

2 Methods

The conterminous US is divided into different regional climate divisions to allow for regional scale analysis of heat waves (see Figure 1). The categorization of these regional climate divisions follows the convention of the National Climate Assessment (Melillo et al. 2014).

2.1 MERRA Dataset

The reference dataset employed is the Modern Era-Retrospective Analysis for Research and Applications (MERRA) reanalysis. The variables obtained from the MERRA reanalysis include precipitation, evaporation and soil moisture, latent and sensible heat flux, are used to understand the physical mechanism associated with heat
waves. However, we use the 2-m temperature dataset, introduced by Wang and Zeng (2013), based on MERRA reanalysis, to identify extreme days and heat waves. This dataset has been bias-corrected in both monthly-mean maximum and minimum surface air temperature using Climate Research Unit (CRU) data and labeled as MERRA-cru hereafter. It performs well in comparison with in situ hourly measurements and much better than the original MERRA reanalysis (Wang et al. 2013). It has 1-hour temporal resolution, global coverage at 0.5° latitude/longitude.

2.2 NARCCAP Data

The NARCCAP was designed to provide the high-resolution needs of regional climate projections of the North America and to evaluate uncertainties associated with regional climate models and global climate models (Mearns et al. 2012). In this work we use RCM-simulated temperature output from NARCCAP Phase-I project, forced by the National Center for Environmental Prediction/Department of Energy (NCEP/DOE) reanalysis as boundary conditions. The NARCCAP Phase-I simulation spans from 1979-2004, the period of 1980-2000 is used in this study. The spatial resolution for the NARCCAP RCMs is 50-km and covers most of North America and some of the adjacent Pacific and Atlantic Ocean and the temporal resolution was 3-hours.

2.3 Heat Waves and Heat Wave Statistics

Definitions of heat waves are often ambiguous and inconsistent (Perkins and Alexander 2013). We follow the heat wave definition in Perkins and Alexander (2013). Heat waves are defined as events of at least three consecutive days above the criteria CTX90pct, where CTX90pct is the 90th percentile of daily maximum temperature (Tmax) based on a 15-day window of that calendar day. This threshold is different for each day.
of the year to account for the seasonal cycle. The 15-day moving window accounts for temporal dependence while allowing for a reasonable large sample size. Note the threshold is different for each different day at each grid.

Different metrics of heat waves are considered, including heat wave magnitude (HWM), defined as the average daily magnitude across all heat wave events within a year; heat wave amplitude (HWA), defined as the hottest day of the hottest yearly event; heat wave number (HWN), defined as the number of heat waves within that year; heat wave duration (HWD), defined as the length of the longest yearly event; and heat wave frequency (HWF), defined as the sum of participating heat wave days (Perkins and Alexander 2013). All five metrics are calculated during the summer season of June, July and August (JJA, 92 days in total).

2.4 Large-Scale and Local Conditions

The temperature prognostic equation reveals that the local rate of change in temperature is the sum of horizontal temperature advection, a local energy term involves the latent heat release associated with phase change and sensible heat flux and radiative source term, see equation below.

$$\frac{\partial \theta}{\partial t} = -\mathbf{U}_j \frac{\partial \theta}{\partial x_j} - \frac{L E}{\rho C_p} \frac{\partial (u_j \theta')}{\partial x_j} - \frac{1}{\rho C_p} \frac{\partial Q_i}{\partial x_j}$$

where term I is the horizontal advection that mainly impacted by the large scale meteorological pattern; term II represents the change in local energy partitioning, including the latent heat release associated with phase change and the divergence of sensible heat flux; term III is associated with radiation divergence. The relative
contribution from large and local scale processes to heat wave formation can be evaluated by examining the advection pattern (term I) and changes in local energy partitioning (term II). Adiabatic heating associated with subsidence can warm the planetary boundary layer through entrainment processes and it is included in term II.

To investigate the large-scale processes associated with heat waves, we analyze the 500-hPa geopotential height anomaly (Zg500), sea level pressure (SLP) anomaly, temperature (T2) and surface wind fields during the time when heat waves occur in each climate division. Specifically, we take into account heat wave events at each grid points within each climate division. The corresponding geopotential height anomaly, sea level pressure anomaly and mean surface air temperature, associated with heat waves at each grid point within a climate division, are then aggregated and averaged for the climate division.

Antecedent 90-day temporal evolution of surface variables that are involved in land atmosphere interactions are considered to evaluate their contribution to heat wave formation. We will describe the procedure using precipitation as an example. Specifically, when a heat wave event occurs at a grid point in a certain climate division, the preceding 90-day anomalies of precipitation with respect to the daily climatology at the grid point is extracted and stored (i.e., 1-dimensional, 90-day time series). Then, all heat wave events that occurred at the specific grid point are considered and the corresponding anomalies are averaged across these events. The same procedure applies to all other grid points within the climate division, anomalies of precipitation for all grid points in the climate division are averaged to represent the antecedent temporal evolution of precipitation for the climate division. In the end, a time series of 90-day precipitation anomaly at each
climate division is obtained. A similar procedure applies for soil moisture (SM), evapotranspiration (ET), latent heat flux (LH) and sensible heat flux (SH). However, due to the different soil depth used in the NARCCAP ensemble and the MERRA, which makes it difficult to compare anomalies in soil moisture directly and only possible in a relative sense, we use a normalization procedure. Specifically, the anomalies in soil moisture are normalized with respect to the maximum of the absolute value of each time series to make sure the normalized value ranges from -1 to 1.

3 Results

We first evaluate the ability of the NARCCAP ensemble models to correctly simulate the temperature extremes. As shown in Figure 2, temperature extreme, as represented by the 90th percentile of daily maximum temperature, on average is about 36 °C for the US. The NARCCAP ensemble overestimates temperature extreme by ~2.5 °C over the US. The overestimation is most obvious in the Midwest and central Great Plains, by about 3.8 °C.

3.1 Large-Scale and Regional-Scale Heat Wave Mechanisms

Various aspects of the synoptic environment associated with heat waves can be highlighted by investigating the anomalies against climatology. Figure 3 displays the composite analysis of selected meteorological variables during heat wave events at each climate division from the MERRA data. In general, when a heat wave occurs there is a positive Zg500 anomaly centered over the climate division, which is consistent with previous studies (Lau and Nath 2014; Loikith et al. 2015). Adiabatic heating associated with the mid-level high therefore should contribute to heat waves throughout the continental United States and thus it is not considered in the following analysis.
**Northeast.** In MERRA, over the Northeastern US, heat waves are associated with SLP high centered to the southwest of the Northeast climate division which induces southwesterly flow (Figure 3b). As a result, the warm continental air mass (Figure 3c) is advected to the Northeast climate division. Soil moisture gradually dries due to precipitation deficit, and evapotranspiration deficit occurs accordingly (Figure 4a). As a result, more (less) energy is partitioned into sensible (latent) heat flux (Figure 5a). Therefore, heat waves in the Northeast are formed under both large scale warm air advection (i.e., term I in Equation (1)) and local scale impact (term II).

The NARCCAP ensemble shows a similar pattern of southwesterly winds, indicating that the model captures the warm air advection for heat waves in the Northeast climate division (Figure 6c), although the 2m temperature in NARCCAP is significantly overestimated when compared to MERRA. The antecedent temporal evolution of precipitation, evapotranspiration and soil moisture anomalies are well represented by the model ensemble, with correlation coefficients of 0.4, 0.7 and 0.75, respectively. The model ensemble underestimates precipitation and ET anomalies (Figure 4a) and leads to less increase (decrease) in sensible (latent) heat flux (Figure 5a), indicating underestimating of the local contribution to heat waves (term II). On the other hand, the wind is traversing a much warmer terrestrial region in NARCCAP and advecting this very warm air into the Northeast (Figure 6c), which explains why the NARCCAP ensemble is overestimating the temperature extremes (Figure 2).

**Southwest.** Regionally, the SLP shows a negative anomaly off the California coast and a positive anomaly to the north and northeast in MERRA (Figure 3e). The wave pattern of Zg500 anomaly is similar to that in Lau et al. (2012), which suggests that this
blocking feature tends to impede the passage of synoptic disturbance, as evidenced by the wind pattern (Figure 3e, 3f). This blocking pattern acts to slow down the climatological maritime advection of relative cool air inland (term I) and aids to enhance local warm air temperature (term II).

Due to the dry climate in the Southwest, precipitation and ET changes little (Figure 4b). Energy partitioning shows slight increase (decrease) in sensible (latent) heat flux (Figure 5b). Hence, heat waves in the Southwest are attributed to large-scale blocking patterns that limit the inland penetration of cool air, along with the strong local contribution of sensible heat flux due to its semi-arid climate.

The NARCCAP ensemble generally captures the regional SLP anomaly pattern but the magnitude and spatial extent of the positive anomaly is overestimated (Figure 6e), so is the mean temperature pattern (Figure 6f). Temporal evolution of precipitation and ET are well captured (Figure 4b). Latent heat flux and sensible flux from the MERRA are within the ensemble range (Figure 5b).

**Midwest.** For the Midwest climate division, Zg500 positive anomaly overlaps with the positive Tmax anomaly from the MERRA data (Figure 3g). The SLP pattern shows negative (positive) SLP anomaly to the northwest (southeast) of the climate division (Figure 3h). Due to presence of the pressure gradient, a southerly wind component forms and brings warm air from the south into the Midwest, indicating warm air advection may be partly responsible for heat waves over the Midwest (term I). Similar to the Northeast, soil moisture is less than its climatological value and gradually dries out, due to precipitation deficits. Evapotranspiration is also less than its climatological value (Figure 4c).
Compared to MERRA, the NARCCAP ensemble underestimates the local contribution (term II) with less sensible heat flux anomaly (Figure 5c). Zg500, and SLP and Tmax anomaly in the NARCCAP show very similar patterns. However, surface air temperature is much warmer in the NARCCAP (see Figure 3i, 6i), for this reason southerly and southwesterly winds bring much warmer air that has traversed a large terrestrial region, to the Midwest in the NARCCAP as compared to the MERRA. This explains the overestimation of temperature extreme in the Midwest (Figure 2).

**Great Plains.** Over the southern Great Plains, a negative SLP anomaly is collocated with a midlevel positive Zg500 anomaly in MERRA (see Figure 3j, 3k). Southerly wind is associated with warm air advection (term I, see Figure 3l). Surface wind anomaly shows a convergence pattern with winds moving towards Texas and Oklahoma (Figure 3l). This indicates that heat waves over the Southern Great Plains are associated with low level convergence which is likely due to a thermal low induced by drying the soil moisture and high temperatures over this region.

Precipitation, ET and soil moisture show very clear decreasing trends in the days leading up to the heat wave (Figure 4d). Sensible heat flux increases by ~30 Wm$^{-2}$ while latent heat flux decreases by about the same amount (Figure 5d). Owing to its transitional climate, variation in energy is most sensitive as compared to other climate divisions (term II).

A similar Zg500, and SLP anomaly pattern is shown in the NARCCAP ensemble, indicating that the ensemble realistically captures the synoptic forcing associated with heat waves in the Southern Great Plains (Figure 6j, 6k, 6l). NARCCAP also reveals the low-level convergence, although with slightly different wind anomaly patterns than
MERRA. Similarly, mean temperature field in the NARCCAP ensemble is overestimated as compared to MERRA. The temporal evolution of terrestrial variables is also well represented by the ensemble (Figure 4d), with correlation coefficients of 0.84, 0.97 and 0.98 for precipitation, ET and soil moisture, respectively. Energy fluxes are well within the ensemble range (Figure 5d).

**Southeast.** For the Southeast climate division, SLP pattern shows a continental low to the northeast of the US, accompanied by southerly winds (Figure 3n, 3o) that are associated with warm southern air masses (Figure 3o). The mean temperature patterns in Figure 3o reveal that relatively warmer air from the Gulf of Mexico may contribute to the heat waves in the Southeast climate division (term I).

Similar to the Northeast and Midwest, local sensible heat flux is significantly underestimated in the Southeast (term II, see Figure 5e). The overall spatial pattern of Zg500, SLP and wind anomaly agree well, except for the overestimation of the mean temperature field, when compare the NARCCAP ensemble with the MERRA in this climate division (Figure 3o, 6o).

**Northwest.** For the Northwest climate division, the SLP anomaly pattern presents a sharp gradient along the northern Rocky Mountains (Figure 3q). The wind and wind anomaly pattern (Figure 3r, 3q) shows that climatological westerly wind reduced by the SLP anomaly, reducing the cool maritime air advection (term I). In NARCCAP, the SLP pattern changes wind direction (Figure 6r) and leads to easterly downslope winds. Topography may play an important role here since the easterly wind originates east of the higher elevation mountains and then descends with adiabatic heating, partly explaining the overestimation of temperature in the Pacific Northwest. The overall pattern of Zg500,
SLP and wind anomaly in the NARCCAP ensemble are very well represented, lending confidence to the physical representation of the models.

There is no obvious trend in ET or precipitation in the Northwest climate division (Figure 4f). Energy partitioning shows that sensible heat flux increases slightly (Figure 5f). Interestingly, both sensible and latent heat flux are positive when close to heat wave, possibly due to increases in net radiation by the clear sky.

In conclusion, in all climate divisions, except those in the western US, heat waves are strongly correlated with antecedent soil moisture conditions. This is also supported by the west-east gradient of correlation between the antecedent 3-month Standardized Precipitation Index and the number of hot days as shown in Mueller and Seneviratne (2012). In the Northeast and Midwest, warm air advection with much warmer terrestrial airmass in the NARCCAP is likely responsible for the overestimation of temperature extremes. In the southern Great Plains and the Southeast, warm air advection is associated with moderate oceanic airmass from the Gulf of Mexico. Key mechanisms for each climate division are summarized in Table 1.

3.2 Extreme Temperature and Heat Wave Metrics

Different heat wave metrics, in terms of temporal evolution and quantile distribution for each climate division, from both MERRA and the NARCCAP, are investigated. For the temporal variation, we will focus on HWA and HWD since amplitude and persistence of a hot spells are the most relevant to human health (Anderson and Bell 2011). For each climate division, all grid points within that specific climate division are considered and then averaged to represent the division value when
calculating the heat wave metrics. Figure 7 & 8 shows the inter-annual variation of summertime HWA and HWD for each of the climate division.

Several heat wave events that occurred in the United States are reflected by the heat wave metrics with the MERRA-cru dataset. For instance, 1980 heat wave that occurred in the Midwest and Southern Great Plains was well captured by the amplitude and duration. The intense heat spells in combination with the drought of 1988, is clearly represented by both heat wave amplitude and magnitude in the Midwest. The heat wave occurred in the eastern US in 1999 is also represented by the relatively high amplitude and magnitude in the Northeast and Southeast (Figure 7 & 8).

Overall, heat wave amplitude in NARCCAP is overestimated as compared to MERRA-cru, in accordance with NARCCAP’s overestimation of high temperatures. In general, the NARCCAP ensemble captures the inter-annual variability of summertime HWA and HWD very well, with correlation coefficient greater than 0.7 for most of the climate divisions, lending confidence to the ensemble models’ ability to represent temporal variability of the heat wave metrics.

To evaluate the NARCCAP ensemble’s ability in representing the spread of heat wave metrics within each climate division, box plots for each heat wave metric are shown in Figure 9. Note that for the NARCCAP ensemble, heat wave metrics from each ensemble member are considered and this results in a much wider spread than the MERRA-cru data. In general, HWA median is overestimated by the NARCCAP ensemble, the inter-quantile range overlaps in all but the Midwest and Northeast regions. A similar behavior is also seen in the HWM. On the other hand, HWD and HWN are well represented in the NARCCAP ensemble (all inter-quantile ranges overlap except HWN.
for the Northeast), whereas HWF is well represented in some climate divisions, for example the Great Plain, Northwest and Southwest but poorly in others, such as the Northeast and Midwest.

In terms of climate division, Northeast seems to be problematic, the NARCCAP ensemble overestimates HWA and HWM, while underestimates HWN and HWF. Similarly, for the Midwest HWA and HWM are overestimated while HWF is underestimated. HWN and HWD are slightly underestimated. The poor performance in amplitude and magnitude in the Northeast and Midwest may be partly explained by the strong overestimation of heat extremes, in association with the warm air advection of much warmer temperature from terrestrial regions in the NARCCAP ensemble than in the MERRA, as shown earlier. In years with a large number of heat waves (e.g. 1988) NARCCAP tends to underestimate the heat wave frequency in the Northeast and Midwest (not shown). Heat wave metrics in the Southwest, Great Plains, Southeast and Northwest are well represented by the NARCCAP ensemble.

4 Discussion and Conclusion.

Extreme heat has been linked to increased risks to health, wild fires, and even heat-related mortality (Haines:2006bh; Vanos:2014cr; Semenza et al. 2009), it is often associated with detrimental socio-economic losses (Kunkel et al. 1999). Heat waves are a result of both large-scale and regional-scale processes, and understanding the synergies between these scales is critical for correctly representing heat waves in atmospheric models. This is particularly important when using these models to project future changes in extreme heat events.
In this study – we use MERRA to understand both the large-scale and regional-scale conditions related to the formation of heat waves. We then analyze NARCCAP Phase I simulations to evaluate the performance of the models in simulating heat wave events throughout the US.

Large scale meteorological patterns associated with heat waves for each climate division have been analyzed. A positive geopotential height at 500-hPa is always present over the climate division when a heat wave occurs. The positive anomaly pattern is robust and has been shown in numerous studies (Lau and Nath 2012; 2014; Loikith et al. 2015), suggesting that this synoptic condition has an important role in controlling the occurrences of heat waves across the US. Heat waves in different climate divisions are induced by different mechanisms. Specifically, the Northeast, Midwest are associated with warm air advection from terrestrial regions; the Southeast is also influenced by warm air advection but from the Gulf of Mexico; the Great Plains is associated with thermal low and convergence at the low levels, indicating the importance of local contribution to heat waves; reduced advection of maritime cool air inland penetration, induced by large-scale meteorological patterns are responsible for heat waves in the Northwest and Southwest.

The temporal evolution of the antecedent 90-day surface variables in MERRA reveals that antecedent soil moisture, precipitation and evapotranspiration deficits are shown in the moderate climate divisions and anomalies in latent and sensible heat flux are most obvious in the transitional climate such as the Great Plains. In addition to the large scale synoptic forcing, large increases in sensible heat flux induced by antecedent soil moisture are also key in the formation of heat waves in this region. The large scale
meteorological patterns are remarkably well represented in the NARCCAP, temporal evolution of antecedent terrestrial variables including precipitation, evapotranspiration, latent and sensible heat flux are also well captured by the NARCCAP ensemble, lending confidence to the ability of NARCCAP ensemble in representing physical processes with heat extremes throughout the United States.

Considering different metrics of heat waves, MERRA clearly captures historical heat wave events that occurred in the United States. Comparing the NARCCAP ensemble to MERRA, the NARCCAP captures the interannual variability of HWA and HWD relatively well, both in terms of temporal evolution and spatial distribution.

HWA and HWM have been overestimated by the NARCCAP ensemble as evidenced by the greater magnitude of the inter-quantile. On the other hand, even though the NARCCAP ensemble tends to overestimate extreme temperature, HWD, HWN and HWF are well represented, which lends confidence in the spatial representation of these heat waves aspects. In terms of spatial representation of the climate regime, the Northeast and Midwest are among the poorly performing regions. The low representativeness of the NARCCAP in the Northeast and Midwest might be due to the warm air advection over-estimation of warm air land surface temperatures in the NARCCAP ensemble.

In summary, even though the NARCCAP ensemble overestimates extreme temperature over the United States, especially over the eastern side of the country. It shows merits when considering the inter-annual variability of heat wave metrics. Spatially, heat wave metrics from MERRA are within the NARCCAP ensemble, except for the Northeast and Midwest which consistently over or underestimate the heat wave metrics.
Acknowledgement

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Tables

Table 1: Summary of mechanisms of heat waves in each climate division in MERRA and the ability of NARCCAP ensemble model to represent each mechanism. In the last column, “over” indicates overestimation, “under” indicates underestimation and “~” indicates of similar magnitude.

<table>
<thead>
<tr>
<th>Region</th>
<th>Primary mechanisms in MERRA</th>
<th>NARCCAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>1. warm air advection with terrestrial source</td>
<td>over (higher surface T)</td>
</tr>
<tr>
<td></td>
<td>2. energy partitioned more to sensible heat flux</td>
<td>under</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1. reduced cool advection of maritime airmass</td>
<td>over (reduced wind speed &amp; higher surface T)</td>
</tr>
<tr>
<td></td>
<td>2. surface energy contribution is negligible</td>
<td>~</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td></td>
</tr>
<tr>
<td>Southwest</td>
<td>1. warm air advection with terrestrial source</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. energy partitioned more to sensible heat flux</td>
<td>over (higher surface T)</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td>under</td>
</tr>
<tr>
<td>Midwest</td>
<td>1. warm air advection with terrestrial source</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. energy partitioned more to sensible heat flux</td>
<td>over (higher surface T)</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td>under</td>
</tr>
<tr>
<td>GreatPlains</td>
<td>1. energy partitioned more to sensible heat flux</td>
<td>~</td>
</tr>
<tr>
<td></td>
<td>2. warm air advection with oceanic source</td>
<td>over (higher SST)</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td></td>
</tr>
<tr>
<td>Southeast</td>
<td>1. warm air advection with oceanic source</td>
<td>over (higher SST)</td>
</tr>
<tr>
<td></td>
<td>2. energy partitioned more to sensible heat flux</td>
<td>under</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1. reduced cool advection of maritime airmass</td>
<td>over (reverse wind pattern &amp; higher surface T)</td>
</tr>
<tr>
<td></td>
<td>2. surface energy contribution is negligible</td>
<td>~</td>
</tr>
<tr>
<td></td>
<td>3. adiabatic heating (subsidence)</td>
<td></td>
</tr>
</tbody>
</table>
Figures

Figure 1: Geographic delineation of the different climate division over the Continental US, dot represents the geographic location of the 100-most populous cities across the US.
Figure 2: On the left, temporally averaged 90\textsuperscript{th} percentile of the maximum temperature time series for a) MERRA-cru dataset. On the right, difference in the 90\textsuperscript{th} percentile of maximum temperature between MERRA-cru and the NARCCAP ensemble, positive value indicates overestimation in the NARCCAP ensemble.
LSMP from MERRA
Figure 3: Large scale meteorological pattern (LSMP) associated with heat waves in each climate division using the MERRA dataset. Specifically, when heat wave occurs over the Northeast (a) is the maximum temperature anomaly (shaded) with respect to its 90th percentile overlapped with the 500-hPa geopotential height (Zg_500) anomaly (contour) with respect to its climatology; (b) shows the sea level pressure (SLP) anomaly and wind anomaly with respect to its climatology; (c) shows the 10m wind when heat wave occurs with respect to its climatology (vector) and surface air temperature (shaded). The following are same as (a), (b) and (c) but with (d), (e) and (f) for Southwest climate division; (g), (h) and (i) for the Midwest; (j), (k) and (l) for the Great Plain; (m), (n) and (o) for the Southeast; (p), (q) and (r) for the Northwest climate division.
Figure 4: Temporal evolution of preceding 90-day normalized antecedent soil moisture anomaly (black) from MERRA (solid) and NARCCAP ensemble (dash). Similarly, for evapotranspiration (blue), and precipitation (red) anomaly in unit of mm/day.
Figure 5: Similar as Figure 4, but for latent heat flux (LH) and sensible heat flux (SH), in unit of Wm\(^{-2}\). The shaded area indicates the NARCCAP ensemble range, and dash line is the NARCCAP ensemble mean.
Figure 6: Same as Figure 3, but with the NARCCAP ensemble dataset.
Figure 7: Inter-annual variation of heat wave amplitude (HWA) in different climate divisions from the MERRA-cru and the NARCCAP ensemble.
Figure 8: Same as Figure 7, but for heat wave duration (HWD).
Figure 9: Boxplot of HWA, HWM, HWN, HWF and HWD for different climate divisions. Specifically, it indicates the spatial representation of NARCCAP ensemble comparing to the MERRA-cru data.