MONITORING REGIONAL-SCALE SURFACE HYDROLOGIC PROCesses USING SATELLITE REMOTE SENSING

by

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As members of the Final Examination Committee, we certify that we have read the dissertation prepared by Abdullah Faizur Rahman entitled Monitoring regional-scale surface hydrologic processes using satellite remote sensing and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

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Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copy 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.

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STATEMENT BY AUTHOR

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DEDICATION

To All People Of This Planet Who Strive Their Best For The ‘Hasanaat’ Of ‘Dunya’ And ‘Aakhira’.
<table>
<thead>
<tr>
<th>TABLE OF CONTENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF ILLUSTRATIONS</td>
</tr>
<tr>
<td>ABSTRACT</td>
</tr>
<tr>
<td>INTRODUCTION</td>
</tr>
<tr>
<td>Context of the problem</td>
</tr>
<tr>
<td>Dissertation format</td>
</tr>
<tr>
<td>Site description</td>
</tr>
<tr>
<td>PRESENT STUDY</td>
</tr>
<tr>
<td>Summary of important findings</td>
</tr>
<tr>
<td>Conclusion and recommendation</td>
</tr>
<tr>
<td>APENDIX A: Regional scale surface flux estimation by combined use of remote sensing and meteorological data</td>
</tr>
<tr>
<td>APENDIX B: On the use of mid-morning remotely sensed and ground-based data to estimate daily evapotranspiration</td>
</tr>
<tr>
<td>APENDIX C: Combining the Penman-Monteith equation with measurements of surface temperature and reflectance to estimate evaporation rates of semiarid grassland</td>
</tr>
<tr>
<td>APENDIX D: An operational approach for vegetation water deficit estimation in a heterogeneous region</td>
</tr>
</tbody>
</table>
LIST OF ILLUSTRATIONS

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Diagram of the study site inside the boundary of Arizona. Walnut Gulch Watershed is also shown in the diagram with the two subwatersheds namely, Kendall and Lucky Hills</td>
<td>16</td>
</tr>
</tbody>
</table>
ABSTRACT

Satellite-based remotely sensed data were used to estimate regional-scale surface energy fluxes and a water deficit index of a semi-arid heterogeneous region in southeast Arizona. Spectral reflectance and radiometric temperature of the surface, derived from the digital counts of TM bands of LANDSAT-5 satellite, were used for this purpose. These reflectance and temperature, along with conventional meteorological information of the region, were used as inputs to numerical models which estimate surface energy fluxes. Point-based meteorological data of the region were spatially extrapolated over a grid of 120 m X 120 m so that it could be used with the spatially continuous remotely sensed data. The water deficit index (WDI) was estimated using surface temperature and a spectral vegetation index, “soil adjusted vegetation index” (SAVI).

The surface fluxes were net radiation flux, sensible heat flux, soil heat flux and latent heat flux. Measured values obtained from the meteorological flux measurement (METFLUX) stations in the study area were compared with the modeled fluxes. Latent heat flux (LE) was the most important one to estimate in the scope of this study. The method of spatially extrapolating the point-based meteorological information and combining with the remotely sensed data produced good estimation of LE for the region, with a mean absolute difference (MAD) of 65 W/m² over a range of 67 to 196 W/m². Also it was found that the numerical models that were previously used to estimate daily LE values from a region using mid-day remotely sensed data (mostly from NOAA-AVHRR) can also be used with the mid-morning remotely sensed data (from
LANDSAT). Out of the two models tested for this purpose (‘Seguin-Itier’ and ‘Jackson’ models), one was found to need some modification so that it could use mid-morning remotely sensed data as inputs. The other was found to be useable as it is, without any modification. Outputs from both models compared well with the measured fluxes from the METFLUX stations. In an effort of estimating the water deficit of the different biomes of the region, WDI of the biomes were estimated. The main goal of this effort was to be able to monitor the surface hydrologic conditions of the region using remotely sensed vegetation and surface information, and minimum ground data. Good estimation of the water deficit condition of the area were obtained by this method. This method was found to be sensitive to a few of the ground information such as wind speed and leaf area index (LAI). It was also found that if the required ground data were correctly estimated, this method could be used as an operational procedure for monitoring the vegetation water stress of the biomes and hence for better management of the region.
CHAPTER 1
INTRODUCTION

Context of the problem

Arid and semi-arid lands cover almost 40% of the earth’s land surface. These lands play an important role in the global water and energy budgets. Among the important characteristics of these lands are the heterogeneity of cover types and also their varied topography. These two important factors contribute to the characteristic atmospheric circulation and spatial surface flux variation that are different from those in the flat homogeneous regions of the earth’s land surface. The numerical hydrological models that have been developed to study the hydrologic processes of the agricultural and forest lands mostly use point measurements of hydrologic parameters. Due to the varied topography and surface conditions, and sometimes due to the lack of easy accessibility, these point-based methods of surface energy flux estimation are not suitable for the arid and semi-arid lands.

Increasing concern over global warming, water shortages and the pressing need for the better management of earth’s existing land resources have spurred research into methods for estimating evapotranspiration (ET) in regional and global scale. As mentioned above, conventional point-based numerical models and field procedures of estimating the ET (as well as other surface fluxes) are not suitable for the arid and semi-arid lands. Hence there is an expressed need to modify the existing procedures and develop new models to solve this problem. In recent years there has been an increased
effort of utilizing satellite based remotely sensed measurements of surface reflectance and temperature as critical model requirements for estimating soil and vegetation status and surface fluxes. Again, most of these efforts were directed towards the agricultural and forest lands due to the direct economic and sociologic impacts that these lands have on our daily life. With the increased understanding that we cannot afford but to look at the earth system as a whole, it is clear that we have to develop similar models and procedures to study the soil, vegetation and surface fluxes of our arid and semi-arid lands. This study was an effort towards that goal.

The study of surface fluxes of arid and semi-arid lands in this research was done using data collected by ground and satellite based sensors from the Walnut Gulch watershed located in the southeast corner of Arizona during an experiment conducted in 1992 (termed as WG'92). This experiment was conducted during the dry, early-monsoon, mid-monsoon, post-monsoon, and “drying” seasons (from April through November 1992). It was designed to acquire remotely sensed data in the visible, near-infrared (NIR), thermal and microwave wavelengths from a variety of ground, aircraft and satellite platforms. Concurrent measurements of soil moisture, vegetation growth and energy and water fluxes were also acquired. This watershed was chosen due to its long history of remote sensing experiments and the presence of extensive hydrologic instrumentation within the watershed. Though aircraft and satellite coverage was extended over the entire watershed and beyond to cover the southeast corner of Arizona, most of the ground-based measurements were limited to two sites within the watershed. Those two were Kendall and Lucky Hills.
WG'92 was a multidisciplinary experiment. Scientists from the University of Arizona departments of 'Soil Water and Environmental Science', 'Hydrology and Water Resources', and 'Optical Science' and also from the United States Department of Agriculture - Agricultural Research Service (USDA-ARS) Southwest Watershed Research Center (SWRC) in Tucson took part in this experiment. A vast data set was collected during WG’92 with an expectation of understanding the regional surface processes of arid and semi-arid lands, and especially of the WG watershed and the southeast corner of Arizona. The present study addresses only a specific aspect (i.e., the surface energy fluxes, specifically ET) of the different complex regional surface processes and hence uses only a part of the data that were collected during WG’92.

Dissertation format

Four research papers appended to this dissertation constitute its main body. Data from WG’92 were used in these papers. The author was directly involved in the collection and processing of the relevant data used in all four papers. Planning of the data collection was mainly done by Dr. Susan Moran, the dissertation advisor of the author.

All the processing of satellite data used in the first paper (Appendix A) was done by the author. Also the meteorological data from the thirteen weather stations from Arizona and New Mexico and the digital elevation data of the area were collected and processed by the author with the active help from Dr. James C. Washburne of the Hydrology and Water Resources department at the University of Arizona. Spatial extrapolation of ground-based meteorological data needed some extra effort of writing
scripts using MATLAB software. Analyses of the data and write-up of the paper was done by the author with the constant guidance from his advisor. The original contribution in this paper was the development and successful use of the extrapolation scheme of the meteorological data for a heterogeneous land so that the point-based meteorological data could be used with the inherently continuous satellite data.

The idea of the second paper (Appendix B) came during the preparation of a research report on the usability of future satellite data for land surface studies. Most of the future earth orbiting satellites will have overpass times corresponding to the mid-morning local standard time (LST), similar to the LANDSAT-TM overpass. Since LANDSAT-TM data was available for the study area, this study was taken up and finally it took the form of a research paper. Ground data were also available from the previous paper (Appendix A). Analyses of the data and the write-up were done by the author. Development of model to be used with the mid-morning satellite data for the purpose of daily ET estimation from range lands was the original contribution of this paper.

Initiation and development of the basic idea behind the third paper (Appendix C), i.e., the ‘Vegetation Index/Temperature’ (VIT) procedure of estimating ET, was done by Dr. Moran. The theories of this paper had been previously examined using data collected from agricultural lands. Since the biome data of southeast Arizona was collected by the author and also the surface temperature and vegetation index data for the study area was available to the author, it was a matter of interest to check the usability of the VIT procedure with the grassland data from WG’92. Hence, this paper was made possible by an active cooperation between Dr. Moran and the author. Data processing and
preparation of all the visual graphs and maps relating to the satellite data were done by
the author and the write-up was done by Dr. Moran. Successful use of Penman-Monteith
theory of evapotranspiration to a partially vegetated surface without a-priori knowledge of
the percent vegetation cover and canopy resistance was the original contribution of this
paper.

The fourth paper (Appendix D) was a logical extension of the third paper. The
intention was to check if the VIT procedure could be used as an operational tool for the
management of arid and semi-arid lands. All the required data were available to the
author. A newer and improved version of biome data for the study area was collected by
the author with the help of Dr. Washburne and that was used for this paper. VIT
procedure and resulting ET maps of the whole study area was produced. Analyses of data
and the write-up of the paper was done by the author. The original contribution of this
paper was to develop the VIT procedure into an operational tool for the management of
arid and semi-arid lands.

Site description

The study area for this research was an 185 km by 251 km rectangular region
(UTM coordinates of the upper left corner being 523646 E, 3586181 N) in the southeast
corner of Arizona (Figure 1). This region is characterized by mountains, valleys and
rivers. Heterogeneous vegetation types such as irrigated agriculture, desert scrub, riparian
vegetation, forests, range lands and others exist in this region. There is also a big dry lake
bed named Wilcox Playa in the north of the region which is almost devoid of vegetation
except for some widely scattered grass and small herbaceous plants. The climate of the whole area is naturally semi-arid. Inside this area, in its southwest corner is the experimental catchment called Walnut Gulch Experimental Watershed (WGEW), operated by the USDA-ARS.

In this region, annual precipitation is 250-500 mm. Two thirds of this falls during a summer “monsoon season” which encompasses the months of July and August. High intensity thunderstorms of limited area extent are characteristic of this region. The USDA-ARS WGEW encompasses the upper 150 km² of Walnut Gulch drainage basin. Topography of the watershed can be described as gently rolling hills incised by rather steep drainage channels. As mentioned in the previous section, Kendall and Lucky hills are two subwatersheds inside this watershed. Kendall is a grass dominated hilly area in the north-eastern corner of WGEW. Lucky hills is a relatively flat area in the north-western edge of the watershed and is mostly bush dominated.

The WG watershed has an excellent network of hydrological instrumentation that was completed in 1966. There are 98 raingages and 11 runoff-measuring stations on the watershed. The raingages are of weighing type with a 20 cm diameter orifice. Also a complete soil map of the area and a digital elevation model (DEM) are available.
Figure 1: Diagram of the study site inside the state boundary of Arizona. Study area is the shaded region in the southeast corner. Walnut Gulch (WG) watershed is in the middle of the region. Kendall and Lucky Hills are shown in the expanded section (Courtesy of Dr. D. C. Goodrich of USDA-ARS)
CHAPTER TWO
PRESENT STUDY

Summary of important findings

The literature review, methods, data, results, discussions and conclusions of this study are presented in the papers appended at the end of this dissertation. The following is a summary of the most important findings in these papers.

Paper # 1: Satellite-based remotely sensed data are spatially continuous. Ground based meteorological data from the conventional weather stations are point based. Hence there is an inherent problem in combining the point based data with the remotely sensed data for any surface energy balance studies. For homogeneous regions, linear extrapolation of model parameters to a spatially continuous grid can be used to overcome this problem. This is not possible for heterogeneous regions. Simple linear extrapolation of model parameters do not take into account the non-linear relations between energy balance components and surface related parameters such as aerodynamic roughness, atmospheric stability and topography. So there is a need to develop methods to extrapolate and upscale the existing surface energy balance (SEB) models so that remotely sensed continuous data and spatially distributed data can be used as model inputs to estimate regional scale surface fluxes.

The relation between meteorological parameters and elevation was utilized to extrapolate the point based data over southeast Arizona. Temporally continuous air
temperature data from thirteen weather stations in and around the study site were interpolated to a point in time same as the time of satellite overpass. DEM of the area was used to derive the sea level air temperature at that time and location. These data were then extrapolated and again DEM was used to regenerate the elevation-corrected air temperature of the area. Similar processes were used for extrapolation of other meteorological data. These data, combined with the satellite data were then used in an existing SEB model that estimates net radiant flux (Rn), soil heat flux (G) and sensible heat flux (H), and then estimates the latent heat flux (LE, can be transformed to ET) as a residual from these three fluxes. SEB map of the study area for four days of the year 1992 were produced in this way. Since there were some error associated with the estimation of Rn, G and H, and since LE was estimated as a residual, there was always a cumulative effect of errors associated with the LE estimation using this SEB model. The fluxes thus produced were then validated with ground based flux data from the WG watershed and also indirectly with other sites inside the study area. This method produced fairly good estimation of surface fluxes, the error levels of which were within the range of the errors found in previous studies of surface flux estimation at local scales in the WG watershed.

**Paper # 2:** There is an escalating shortage of water in the arid and semi-arid regions of the world. To assess and manage this problem, numerous simulation models have been developed to produce daily estimates of regional ET to be used in water balance equation. Some of these models require an extensive database and numerous parameters to run them. But it is not easy to collect an extensive data set from the arid
and semi-arid regions. A practical approach would be to use the models that need few parameters and can be run with easily obtained remotely sensed data. Two such models were available for the estimation of daily ET. They were termed as ‘Jackson’ model and ‘Seguin-Itier’ model in this paper. These models were mainly empirical but had physical basis behind their development. Both of these models were developed and previously tested using mid-day (13:00 - 14:00 LST) remotely sensed data from NOAA-AVHRR and was found to produce good results over agricultural areas.

Since the LANDSAT-TM has a mid-morning (~ 10:30 LST) overpass and our study site was not an agricultural land, two questions arose in using the two above mentioned models for estimating daily ET of the study site. They were: i) do the empirical relations used in these two models work when mid-morning remotely sensed data are used, and ii) what change in the parameters would be needed to estimate ET from non-agricultural areas using these two models. This paper attempted to answer these questions.

The ‘Jackson’ model was found to work well when mid-morning remotely sensed data were used. Daily ET for the Kendall and Lucky Hills sites were estimated using this model and compared with measured daily ET data from these sites. They compared well implying that this model can be used to estimate daily ET of a range land. But it was observed that remotely sensed data should be collected in cloud free conditions. Also, errors associated with instantaneous ET, which was used as an input to this model, needed to be known in order to use this model with confidence.
Some assumptions in the ‘Seguin-Itier’ model were found to need modification so that the mid-morning remotely sensed data could be used as input parameters to estimate daily ET of the range land. Relation between daily and instantaneous values of sensible heat flux was found vary all over the sunshine hours and a correction factor was added to this model to accommodate this variation. Also it was found that the B parameter of this model needed adjustment for each biome under study. When these two factors were taken into account, this model also produced fairly good estimate of daily ET of the range land.

**Paper # 3:** The ‘Penman-Monteith’ numerical model of evaporation estimation is well suited for uniform surfaces such as water, dense vegetation or bare soil. This is not so for the case of heterogeneous surfaces, such as arid and semi-arid lands at the regional scale. Other models that are used for evaporation estimation at regional scale generally require an extensive database of site specific meteorological, plant physiological and soil information. For arid and semi-arid lands, and especially in regional scale, collection of such an extensive data base is very much time consuming, expensive and sometimes even not possible due to inaccessibility. Hence an alternative approach would be to use a simpler model which requires less ground information and remotely sensed spectral data as inputs for model simulations. The approach proposed in this paper was an attempt to use remotely sensed surface reflectance and temperature to allow application of Penman-Monteith theory to partially vegetated fields without a-priory knowledge of the percent cover and canopy resistance. Basically, the Penman-Monteith model was combined with the energy balance equation to estimate the surface temperature associated with four
states of the surface: surfaces characterized by full cover vegetation and bare soil, with ET rates at potential and zero. The relations thus obtained were then linearly interpolated to find the ET rates of intermediate states of vegetation cover. A newly developed concept, termed the ‘Vegetation Index/Temperature (VIT)’ trapezoid, was utilized for this purpose. Remotely sensed spectral and thermal data along with ground based meteorological data, obtained from southeast Arizona in 1992, were used to test this approach of ET estimation.

The approach was tested at two scales, local and regional. ET was estimated using ground based spectral and thermal remotely sensed data in local scale at the grass dominated Kendall subwatershed. For the regional scale, satellite-based remotely sensed data was used to the grasslands in the northeast corner of Arizona. Based of the results of these tests, this approach was found to be reasonable and to have potential for mapping vegetation water stress of heterogeneous landscapes. The important facts in this study were that minimum numbers of input parameters were needed to produce a fairly good estimation of ET and that all these inputs were readily available from the existing data sources. Existing earth-orbiting satellites provided the surface temperature and reflectance data. Plant height, leaf area index (LAI) and roughness data for the specific biomes were obtained from published reports. Meteorological data of the region were readily available from weather stations inside and outside the area covered by the satellite images.

This paper also pointed out that there were different sources of errors for the application of this approach at the regional scale. Effects of topography on extrapolation
of meteorological inputs and also on surface reflectance needed to be further studied in order to apply this approach at a regional scale. It was also found that a correct biome identification would be needed if this approach was to be applied over a large heterogeneous area.

**Paper # 4:** This paper was a logical continuation of the previous one (i.e., paper #3). Since the arid and semiarid lands support multiple biomes in addition to grassland, it was necessary to test if the VIT trapezoid method could be used to estimate ET of different biomes of a heterogeneous land. The overall goal was to apply this approach in an operational manner that would allow monitoring and assessment of heterogeneous arid and semi-arid lands.

Seven distinct biomes were found to characterize the study area. Maximum and minimum plant heights and leaf area indices of these biomes were found from the published reports on these biomes. Topography adjusted and interpolated values of meteorological inputs were produced using data from thirteen weather stations in and around the study site. LANDSAT-TM spectral and thermal data for four cloudless days in 1992 were available for this study.

Results of this study showed that this procedure could be used as an operational tool for monitoring the spatial and temporal vegetation water stress conditions over a heterogeneous and partially vegetated semiarid region. This water stress information could be used to predict range and forest fire potential of the region, animal grazing potential for the grasslands, irrigation scheduling for the agricultural areas etc. Also the
use of a small number of relatively easily available input parameters to run this model simulation validated its use as an operational tool.

Sensitivity analyses of the input parameters showed that this model was mostly sensitive to the variation in wind speed. A more computation- and time-consuming method of spatial wind speed estimation showed that there can be a substantial error in wind speed estimation using the simple interpolation method that was used in this study. Errors in maximum LAI and in vapor pressure deficit (VPD) were also found to cause error in model simulation. Also it was found that the VIT trapezoid of different biomes should be calculated differently to obtain a better result using this model.

Conclusion and recommendation

The results of these experiments showed that remotely sensed satellite data can be combined with the ground-based meteorological data as input parameters to the existing numerical models for successfully estimating the ET and other surface fluxes over a heterogeneous region such as the southeast corner of Arizona. Mid-morning satellite data were found to be useable in these models. Also, it was found that Penman-Monteith equation could be modified to estimate the ET of the partially vegetated surface. This procedure was further found to be useful as an operational tool for monitoring the heterogeneous lands of southeast Arizona. Further investigation in the extrapolation schemes of meteorological parameters, such as wind speed, vapor pressure deficit etc. from point-based measurements to spatially continuous maps in an operational basis, would definitely be useful in reducing the errors in the ET estimation by this procedure.
APPENDIX A:

Regional-Scale Surface Flux Estimation by Combined Use of Remote Sensing and Meteorological Data

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Submitted to “Remote Sensing of Environment”
ABSTRACT

Combination of a surface energy balance (SEB) model, remotely sensed spectral data from LANDSAT sensors and meteorological data from thirteen weather stations resulted in a good estimation of surface energy fluxes over a semiarid heterogeneous region as verified at several independent locations in south-east Arizona. For latent heat flux (LE), the mean absolute difference (MAD) between the measured and modeled fluxes was 65 W/m$^2$ over a range of 67 to 196 W/m$^2$. A new technique was used to spatially extrapolate point-based meteorological data over a heterogeneous region to make them compatible with satellite-based distributed data.

INTRODUCTION

Several well accepted mathematical models currently exist that can simulate point- or local-scale (1 m$^2$ to 10 km$^2$) surface energy balance (SEB) and mass transfer processes (Monteith, 1965). These models have been revised to utilize remotely sensed data as inputs to estimate sensible and latent heat fluxes (Moran and Jackson, 1991). They were successfully applied to mature agricultural fields using ground, aircraft and space-based sensors (Moran et al. 1993). With recent advances in the estimation of resistance to heat transfer, the local-scale SEB models have also provided reasonable estimates of surface fluxes for heterogeneous range lands with very sparse vegetation (Kustas et al., 1994). In each case however, these models were used to produce point or local-scale estimates of surface energy fluxes.
For homogeneous regions, local-scale estimates of surface energy balance can be safely extended to regional-scale by simple extrapolation of model parameters. But for heterogeneous regions this procedure may be insufficient (Blyth and Dolman, 1993). Simple linear extrapolation of model inputs and outputs do not take into account the non-linear relations between energy balance components and surface related parameters, such as aerodynamic roughness, atmospheric stability, and topography. So, there is a need to develop methods to extrapolate and upscale the existing SEB models so that remotely-sensed and spatially-distributed data can be used as model inputs to estimate regional-scale surface fluxes. The objective of the present study was to use remotely sensed spectral data and regional meteorological data as input parameters to an SEB model to estimate regional-scale (covering a 100 km$^2$ area) surface energy fluxes of a semiarid region in southeastern Arizona.

DATA

The study area was an 185 km by 251 km rectangular region (UTM coordinates of the upper left corner of the area is 523646, 3586181) in the southeast corner of Arizona (Figure 1). This region is characterized by varied topography (mountains, valleys and rivers) and heterogeneous vegetation (irrigated agricultural fields, desert scrub, riparian vegetation, mountain forests, range lands and others). There was also a dry lakebed (Wilcox Playa) in the region which was almost devoid of any vegetation except for some widely scattered grass and small herbaceous plants. The climate of the area is naturally semiarid.
In 1992, an experiment, termed Walnut Gulch ’92 (WG ‘92) was conducted in the Walnut Gulch Experimental Watershed, a watershed in the above-mentioned study area maintained by USDA-Agricultural Research Service (Moran et. al., 1993). Eight LANDSAT Thematic Mapper (TM) images of the region were acquired as a part of this effort over a period of nine consecutive months. Measurements of atmospheric optical depth and water vapor content were made during each overpass to allow retrieval of surface reflectance and temperature from TM images.

Meteorological data were obtained from thirteen weather stations (see Table 1 for their names, UTM coordinates and elevation. Figure 1 is also marked according to the serial number of stations form Table 1). In addition, digital maps of vegetation types at 1 km resolution and land surface elevation at 120 m resolution, which was resampled from 90 m, were also available for the entire study area. Digital maps of vegetation were obtained from prototype land cover characteristics data base for conterminous United States, developed by US Geological Survey (USGS) and EROS Data Center (Loveland and Scholtz, 1993). Digital elevation data for the region were obtained from USGS data base (US Dept. of Interior, 1990).

Ground-based energy flux measurements were made at two selected sites, namely Lucky Hills and Kendall, in the study area. UTM co-ordinates and elevations of these sites are given in Table 1. Meteorological and flux (METFLUX) stations, containing instrumentation for measuring both general meteorological conditions and estimating surface energy balance were deployed at these two sites (for information about
METFLUX stations, see Stannard et al., 1994). Data were collected on an hourly basis. Lucky Hills was a mildly sloping, shrub-dominated area. Kendall was hilly and mostly grass-dominated. Data from day(s) of year (DOY) 162, 178, 274 and 306 were used for analyses in the present study. These four days were characterized by clear sky conditions. DOY 162 and DOY 178 occurred during the early monsoon season, DOY 274 was during the wet season. DOY 306 was during the post-monsoon drying season. Even though the DOYs were scattered over a span of four months, there were some anomaly in surface conditions in the area in that year 1992. That year was characterized by a wet pre monsoon and early monsoon, and intermittent rain over the rest of the year, which contrasts to more normal winter (Nov - Jan) and summer (July - Sept) wet seasons.

**THEORY**

Remotely sensed data were used as input parameters in a surface energy balance (SEB) model to estimate such surface fluxes as net radiant flux, sensible heat flux and soil heat flux. Latent heat flux was then indirectly estimated as a residual based on the above mentioned fluxes. The procedure for estimating these fluxes from remotely sensed data and ground-based meteorological information is based on the evaluation of a one-dimensional form of energy balance equation, i.e.,

\[ LE = R_n - G - H \] (1)

where \( R_n \) is net radiant flux density, \( G \) is soil heat flux density, \( H \) is sensible heat flux density, and \( LE \) is latent heat flux density. Values of \( LE, G \) and \( H \) are positive when
directed away from the surface, and that of \( R_n \) is positive when directed towards the surface. Units of all these energy flux densities are in W/m\(^2\).

Net radiant flux density is the sum of incoming and outgoing radiant flux densities, i.e.,

\[
R_n = S(1 - \alpha) + L \downarrow - L \uparrow
\]  

(2)

where \( S \) is incoming solar radiation, \( \alpha \) is the albedo, \( L \) is longwave radiation (> 4\( \mu \)m), and the arrows indicate the flux direction (\( \downarrow \) = incoming, \( \uparrow \) = outgoing). Albedo can be estimated via several methods. For the present study, it was estimated using the approach described by Washburne (1994). An weighted average of visible and near-infrared reflectances were used for this purpose. The weights were derived from prior knowledge of the 'partial/total' ratio of solar radiance intercepted by the TM sensors for the study site. \( S \) can be measured with a calibrated pyranometer. \( L \downarrow \) can be estimated from ground-based measurements of air temperature and vapor pressure while \( L \uparrow \) can be estimated using the radiometric surface temperature obtained from the TM image (Jackson, 1985):

\[
L \downarrow = \varepsilon_a \sigma T_a^4
\]  

(3)

and

\[
L \uparrow = \varepsilon_s \sigma T_s^4
\]  

(4)

where \( \varepsilon_a \) is the effective atmospheric emissivity = 1.24(\( e_o T_o^4 \))\(^{1/7} \) (Brutsaert, 1982), \( \sigma \) is the Stephan-Boltzmann constant (W/m\(^2\)/K\(^4\)), \( T_o \) is the air temperature (K), \( e_o \) is the vapor
pressure (mb), $\varepsilon_s$ is the surface emissivity and $T_s$ is the surface radiometric temperature (K).

$G$ can be estimated by a relation between $G/R_n$ and surface reflectance data in the red and near-infrared (NIR) spectral bands (Kustas et al., 1993):

$$G/R_n = 0.4 - 0.33ND$$

(5)

where ND is the normalized difference vegetation index,

$$ND = \frac{(NIR - Red)}{(NIR + Red)}$$

(6)

a spectral index that indicates the amount of green vegetation present. ‘NIR’ and ‘Red’ are the surface reflectance (%) in ‘near infra-red’ and ‘red’ bands (TM bands 4 and 3) respectively.

The sensible heat flux density ($H$) can be expressed as:

$$H = \rho C_p (T_s - T_a) / r_t$$

(7)

where $\rho C_p$ is the volumetric heat capacity of air ($\equiv 1150 \text{ J/m}^3\text{C}$), and $r_t$ is a stability corrected aerodynamic resistance (s/m) (adapted from Kustas et al., 1989), which is a function of $T_s$, $T_a$, wind speed ($u$), the reference height ($z$), the aerodynamic parameters: surface roughness length ($z_r$) and displacement height ($d$), and $kB^{-1}$ (an expression that accounts for the difference between roughness of heat and momentum transfer). The expression of $r_t$ is as follows:

$$r_t = \left\{ [\ln((z-d)/z_r)] + kB^{-1} - \Psi \right\} [\ln((z-d)/z_r) - \Psi] / k^2 u,$$

(8)
where $\Psi_s$ and $\Psi_m$ are stability correction factors for heat and momentum transfer respectively:

$$
\Psi_s = \exp\{0.598 + 0.39[\ln(-R_i)] - 0.09[\ln(-R_i)]^2\}
$$

(9)

and

$$
\Psi_m = \exp\{0.032 + 0.448[\ln(-R_i)] - 0.132[\ln(-R_i)]^2\}
$$

(10)

$kB'^{-1}$ is calculated as $0.17u(T_s - T_a)$ (Kustas et al., 1989). $R_i$ is a variation of bulk Richardson’s number (Thom, 1972) which can be expressed as

$$
R_i = g(T_a - T_s)(z - h)/T_a U^2,
$$

where $g$ is the acceleration due to gravity (m/s²). $k$ is the von Karman’s constant (0.41) and $u$ is the wind speed. The $d$ and $z_\infty$ terms can be approximated as a function of plant height $h$ (Brutsaert, 1982), where:

$$
d = (2/3)h,
$$

(11)

and

$$
z_\infty = h/8,
$$

(12)

Ten different types of vegetation and vegetation association for the study area were identified from the digital map of vegetation. These were agriculture, alpine forest, conifer forest, creosote-mesquite association, desert grassland, oak-grass association, dry playa, sage-creosote association, sage-grass association and sage-oak association. Plant heights of these different biomes were assigned as 0.75, 15, 15, 3, 0.3, 3, 0.1, 3, 2 and 5 meters respectively. These biomes of the area are shown in figure 2. Surface temperature ($T_s$) was derived from band-6 digital numbers of TM image using a radiative transfer
code (RTC) and radiosonde data (Washburne, 1994). This way, \( R_e \), \( G \), and \( H \) were estimated as described above and \( LE \) was then estimated as residual from equation (1).

**METHOD**

As mentioned before, the objective of the present research was to apply a local-scale SEB model at a regional scale by combined use of spatially continuous remotely sensed data and spatially extrapolated meteorological data. Remotely sensed data are inherently spatially continuous unlike conventional meteorological. To combine the point-based meteorological data with spatially continuous remotely sensed data as input parameters for energy balance models, several new techniques were developed. Procedures of spatial extrapolation of meteorological data over the region will be discussed next. Also, the strategy of deriving ten biome classes over the region will be explained here. As mentioned at the end of the previous section, the maximum vegetation heights among the biomes of the region were that of alpine and conifer forests (15 m). So the reference height for the meteorological parameters were set at 17 m, which is 2 m higher than the maximum biome height of the region.

**Air Temperature:**

Hourly air temperature data from the thirteen weather stations were interpolated to the satellite overpass time (10:15 A.M). Elevations of these weather stations were known (Table 1). Thus, thirteen point-values of temperature, at different elevations and distributed over the region, were obtained for each day of overpass. These distributed temperature values for each day were then normalized to sea level using a static lapse rate
of temperature from radiosonde data acquired at Fort Huachuka Army Base near the WG watershed, and applying it to the elevations of the respective weather stations. A two-dimensional spline interpolation method was then used to make these normalized temperature values spatially continuous at sea level over the whole region at a grid scale of 120 m by 120 m (Rahman et al., 1994). Spline function was used to assure global smoothness in the interpolated data from the irregularly distributed weather stations over the study site. Applying the static lapse rate of temperature with the digital elevation map (DEM) of the region (17 m was added to the DEM of each grid), these gridded temperature maps at sea level were then used to regenerate the spatially continuous air temperature of the region at the reference height (Figure 3). This way a surface-averaged and topography-adjusted air temperature map of the region at the reference height was generated for each day.

Wind speed and vapor pressure:

Hourly wind speed data were collected at all weather stations at a height of 4 m over well watered short grass. These values were interpolated to the satellite overpass time and like air temperature, thirteen spatially distributed point-values were obtained for each day. Since the reference height was set at 17 m, wind speed at each station was vertically extrapolated to reference height using the logarithmic wind profile equation:

\[
  u(z) = \frac{u_*}{k} \ln \frac{z - d}{z_o}
\]

where \( u(z) \) is the wind speed at a height \( z \) (17 m) and \( u_* \) is the friction velocity proportional to the tangential rate of rotation of the frictionally driven eddies in the wind
flow (Thom, 1972). For a given value of $u$, the value of $u^*$ depends on $z_a$. Since all the stations were located over short grass, $u^*$ values over the stations for given wind speeds, at 4 m above ground, were calculated and then the wind speed at 17 m height was estimated using equation 13. Due to the lack of any known method of spatially extrapolating wind speed over a large terrain of heterogeneous surface cover and varied topography, wind speed values at reference height were interpolated between the weather stations over the surface grids (120 m X 120 m) of the region using a simple two-dimensional spline interpolation method. In this way, a map of wind speed over the entire region was prepared for each day.

There was no known technique of extrapolating the vapor pressure values vertically from the acquiring height of 4 m to the reference height of 17 m. Also any method of spatial extrapolation of it over the heterogeneous region was unknown. So, the vapor pressure values at each day at the weather stations (at 4 m height) were interpolated to the satellite overpass time and then spline interpolation method was used to obtain a vapor pressure map of the region for each day.

**Biome designation:**

Originally in the USGS land cover data base (Loveland and Scholtz, 1993), 36 biome associations were recognized in the study area. Table 2 shows these associations with their respective class number, area and percent cover. Since there are overlapping of different biomes in different associations and since in the present study we were concerned more about the biome height than the areal association of different biomes,
these 36 classes were redefined into 10 biome associations based on their potential height. Table 3 shows the grouping strategy for these 10 biome associations. In the original database, the biome names were arranged in the order of relative abundance of the respective vegetation in a spatially continuous area. Table 3 was arranged based on this information, the percentage of land cover by each association and also on personal experience of the authors about the study area.

**TM images and solar radiation:**

TM images were registered using ground control points based on prior research work on the same area (Washburne, 1994). Surface reflectance and temperature were retrieved from LANDSAT TM digital numbers based on on-site measurements of atmospheric and surface conditions made during the overpass. ND maps of the region were produced from the reflectance images using the expressions described in equation (6). Incoming solar radiation was measured at the Kendall site during the satellite overpass each day and these values were taken to be applicable over the entire study area for respective days.

The SEB model, described above, was then used over the region to estimate different fluxes at a grid scale of 120m by 120m. $R_n$, $G$ and $H$ maps were prepared for each overpass day. The final product of this endeavor was the production of $LE$ maps of the region, produced as a residual using equation (1).
RESULTS AND DISCUSSION

Mapped values of the surface energy fluxes at Lucky Hills and Kendall were compared with METFLUX values of the respective fluxes from the same sites. Mean absolute difference (MAD) between modeled and measured (METFLUX) data was used to analyze the goodness of fit of the model. Modeled and measured values of the fluxes are given in Table 4.

Figure 4 shows the comparison of the fluxes for all four days at two sites. MAD between the METFLUX and modeled values of $R_n$ was 109 W/m$^2$ over a range of 459 to 659 W/m$^2$. Modeled values were consistently overestimated. The overestimation was in the range of 10 - 12%. This is probably due to the vapor pressure factor in the incoming longwave estimation (equation (3)). Since the vapor pressure at the weather stations were measured over well watered short grasses, most likely it was higher than that over the dry surfaces of Kendall and Lucky hills. Higher vapor pressure values would overestimate the incoming longwave values and hence overestimate the net radiation. The consistent overestimation of $R_n$ by the model suggests that a continuous overestimation factor was responsible. It may also be useful at this point to appreciate that METFLUX measurement of net radiant flux density can have an error of ±6% (Droppo and Hamilton, 1973), which, translated to the present case, can be 50 W/m$^2$.

MAD for $G$ was 73 W/m$^2$ over a range of 171 to 240 W/m$^2$, and for $H$, it was 26 W/m$^2$ over a range of 117 to 234 W/m$^2$. $G$ was also overestimated by the model. Since $G$ was calculated using $R_n$, this overestimation was partly due to overestimation of $R_n$. 
Also there is a possibility that there might have been some problem with the METFLUX G estimation. Previous studies have shown that for a sparsely vegetated area, in a clear day, G can be up to 0.5Rn (Clothier et al., 1986). But in the present case, METFLUX values of G were 0.16 to 0.35 Rn, which is most probably an underestimation due to some factors not known to the authors. The model resulted in a good estimation of H with a low 26 W/m² MAD.

For LE, MAD was 64 W/m² over a range of 119 to 266 W/m². Since LE was calculated as a residual, the errors associated with the other three components of energy balance equation had a cumulative effect of errors on it. Previous studies with similar data from the same sites have also shown similar results for LE estimation (Moran et al., 1993).

Ground-based measurements were not available at other points of the study area to validate the modeled fluxes for the entire region. To further validate the model performance, LE estimates from different biomes of the area (riparian vegetation, dry playa, forest, agricultural area and grassland) were extracted and compared over four clear overpass days (Figure 5). Except on DOY 178, the highest LE values were found at the forest areas. On DOY 178, agriculture showed the highest LE. Lowest LE values for all DOYs were measured from the dry playa. This trend is in harmony with the surface conditions. Agricultural areas show a peak LE on DOY 178 and then gradual decrease. It is probably due to the fact that the crops were harvested sometime after that date. In semiarid areas, transpiration from vegetation is the main source of LE. So the LE flux in
agriculture decreased after DOY 178. The riparian area showed a gradual decrease in LE values from DOY 162 to DOY 306. This was due to the fact that as the season changed from summer to winter, deciduous riparian vegetation started to lose their leaves, hence decreasing transpiration. The dry playa always exhibited low LE flux due to lack of vegetation. Grassland exhibited a steady rate of LE over the seasons. This is also consistent with the characteristics of the grasslands of the study area. Except for immediately after a heavy rainfall, these grasses remain in a dry condition almost all around the year. So the transpiration characteristic of the grassland also remain fairly constant all year.

It can also be seen in Figure 5 that DOY 162 had higher LE than other DOYs for all biomes except agriculture. The four LE maps in figure 6A-D show that there exists a clear pattern of relatively higher LE values at riparian, forest and agricultural areas and lower values at grasslands and barren areas. The maps also show the temporal variation that occurred in each biome over the turn of the seasons. It is noticeable that DOY 162 had a relatively higher LE flux over the whole area, except the agricultural areas (the darker spots in the mid section of the map). The mountainous areas (right hand side of map) and the upper San Pedro river areas (upper left corner) show higher LE values in DOY 306. But otherwise, the range of LE was also low for DOY 306. These variations in the LE values over the area in different days are clearly visible in these maps.
CONCLUSIONS

This research was aimed at studying surface energy fluxes of a heterogeneous region using remotely sensed spectral data and regional meteorological data as input parameters to an existing SEB model. The objective was to combine spatially distributed satellite remote sensing data with point-based meteorological data through a new technique of spatial extrapolation, and to investigate if this method can produce spatially distributed surface energy fluxes at a regional scale. This approach of regional scale flux estimation using remotely sensed data is a step towards the EOS era when regional ET values will have to be regularly estimated to provide feedback of input into the global scale models for studying the earth system as a whole. (EOS [Earth Observing System] is the core of the ambitious international Mission to Planet Earth [MTPE] program to study the global change using remote sensing techniques). There were some problems with spatially extrapolating some of the meteorological parameters, such as vapor pressure. Consequently this gave rise to estimation errors in the model output. But relatively small MAD values for the validated estimates, and the realistic results of comparative study of LE values over different biomes show that this is a promising procedure for estimation of spatially distributed surface fluxes over a heterogeneous terrain.
ACKNOWLEDGMENT

This research was supported by the NASA Interdisciplinary Research Program in Earth Sciences (NASA Ref. Num. IDP-88-086), the NASA EOS Program (NASA Ref. Num. NAG-W2425) and NSF (BSC-8920851). It was also made possible by the cooperative spirit of Steve Land of EOSAT Corp. who provided LANDSAT TM images at no cost.
REFERENCES


US Department of Interior, USGS, (1990), Digital elevation model, scale 1:250000, *EDC ID: dma0167, dma ID: NI12; 11W, 09W, 08E & 08W.*

Table 1: Locations and elevations of the 13 weather stations from where meteorological data were collected for the present study. Also the description of two subwatersheds, namely Lucky Hills and Kendall are included here. Serial number is included for specifying the positions of the stations in figure 1.

<table>
<thead>
<tr>
<th>Serial No.</th>
<th>Stations</th>
<th>UTM (X)</th>
<th>UTM (Y)</th>
<th>Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Deming</td>
<td>808046</td>
<td>3574650</td>
<td>1316</td>
</tr>
<tr>
<td>2</td>
<td>Douglas</td>
<td>633030</td>
<td>3480137</td>
<td>1267</td>
</tr>
<tr>
<td>3</td>
<td>Safford</td>
<td>623566</td>
<td>3631913</td>
<td>900</td>
</tr>
<tr>
<td>4</td>
<td>Ft. Huachuka</td>
<td>561663</td>
<td>3496097</td>
<td>1438</td>
</tr>
<tr>
<td>5</td>
<td>Gila Bend</td>
<td>339094</td>
<td>3639105</td>
<td>262</td>
</tr>
<tr>
<td>6</td>
<td>Yuma</td>
<td>160403</td>
<td>3618090</td>
<td>65</td>
</tr>
<tr>
<td>7</td>
<td>Phoenix</td>
<td>405177</td>
<td>3699231</td>
<td>337</td>
</tr>
<tr>
<td>8</td>
<td>Tucson</td>
<td>506603</td>
<td>3553550</td>
<td>779</td>
</tr>
<tr>
<td>9</td>
<td>Columbine</td>
<td>602353</td>
<td>3618921</td>
<td>2904</td>
</tr>
<tr>
<td>10</td>
<td>Coronado</td>
<td>556551</td>
<td>3562574</td>
<td>945</td>
</tr>
<tr>
<td>11</td>
<td>Empire</td>
<td>534653</td>
<td>3516033</td>
<td>1418</td>
</tr>
<tr>
<td>12</td>
<td>Muleshoe</td>
<td>568560</td>
<td>3584819</td>
<td>1273</td>
</tr>
<tr>
<td>13</td>
<td>Saguaro Natl. Monument</td>
<td>531340</td>
<td>3577207</td>
<td>945</td>
</tr>
<tr>
<td>14</td>
<td>Lucky Hills</td>
<td>589843</td>
<td>3512239</td>
<td>1363</td>
</tr>
<tr>
<td>15</td>
<td>Kendall</td>
<td>600258</td>
<td>3511498</td>
<td>1521</td>
</tr>
</tbody>
</table>
Table 2: Land cover classification for South East Arizona. 36 biome associations are listed here. Original class number from the USGS data base, area and percent cover for each association in the study area is also shown.

<table>
<thead>
<tr>
<th>Class</th>
<th>Area (sq. km)</th>
<th>Percent Cover</th>
<th>Biome associations</th>
</tr>
</thead>
<tbody>
<tr>
<td>77</td>
<td>3870</td>
<td>20.9</td>
<td>Creosote, Sand Sage, Grama, Wheatgrass</td>
</tr>
<tr>
<td>76</td>
<td>2863</td>
<td>15.5</td>
<td>Sand Sage, Blue Grama, Wheatgrass, Buffalograss</td>
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<tr>
<td>73</td>
<td>2599</td>
<td>14.1</td>
<td>Sand Sage, Creosote, Ricegrass, Blue Grama, Dropseed</td>
</tr>
<tr>
<td>82</td>
<td>1950</td>
<td>10.5</td>
<td>Grama, Buffalograss, Wheatgrass, Creosote, Mesquite</td>
</tr>
<tr>
<td>58</td>
<td>1223</td>
<td>6.6</td>
<td>Bluegrama, Wheatgrass, Buffalograss</td>
</tr>
<tr>
<td>129</td>
<td>979</td>
<td>5.3</td>
<td>Ponderosa Pine, Pinyon Pine, Juiper</td>
</tr>
<tr>
<td>69</td>
<td>979</td>
<td>5.3</td>
<td>Creosote, Saltbush, Sand Sage</td>
</tr>
<tr>
<td>81</td>
<td>973</td>
<td>5.3</td>
<td>Sand Sage, Oak, Blue Grama, Buffalograss</td>
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<td>68</td>
<td>856</td>
<td>4.6</td>
<td>Creosote, Mesquite, Saltbush, Sand Sage</td>
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<td>118</td>
<td>373</td>
<td>2.0</td>
<td>Ponderosa Pine, Douglas Fir</td>
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<tr>
<td>70</td>
<td>278</td>
<td>1.5</td>
<td>Dropseed, Sand Sage, Creosote</td>
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<td>108</td>
<td>222</td>
<td>1.2</td>
<td>Ponderosa Pine, Pinyon Pine, Juniper, Oak</td>
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<tr>
<td>83</td>
<td>221</td>
<td>1.2</td>
<td>Grama, Buffalograss, Wheatgrass, Creosote, Mesquite</td>
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<td>71</td>
<td>167</td>
<td>0.9</td>
<td>Saltbush, Greasewood, Big Sage</td>
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<tr>
<td>89</td>
<td>161</td>
<td>0.9</td>
<td>Oak, Bluestem, Indiangrass, Switchgrass, Juniper</td>
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<tr>
<td>88</td>
<td>155</td>
<td>0.8</td>
<td>Oak, Bluestem, Indiangrass, Mesquite, Juniper</td>
</tr>
<tr>
<td>79</td>
<td>85</td>
<td>0.5</td>
<td>Sand Sage, Creosote, Dropseed, Blue Grama</td>
</tr>
<tr>
<td>111</td>
<td>82</td>
<td>0.4</td>
<td>Ponderosa Pine, Lodgepole Pine, Juniper</td>
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<tr>
<td>75</td>
<td>69</td>
<td>0.4</td>
<td>Greasewood, Sage, Wheatgrass, Needleandthread</td>
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<td>66</td>
<td>60</td>
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<tr>
<td>20</td>
<td>57</td>
<td>0.3</td>
<td>Corn, Soybeans, Pasture</td>
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<tr>
<td>36</td>
<td>53</td>
<td>0.3</td>
<td>Grama, Buffalograss, Wheat, Sorghum</td>
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<tr>
<td>127</td>
<td>43</td>
<td>0.2</td>
<td>Sage, Annual Grasses, Oak, Pine</td>
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<td>80</td>
<td>41</td>
<td>0.2</td>
<td>Blue Grama, Buffalograss, Big Sage, Saltbush</td>
</tr>
<tr>
<td>155</td>
<td>39</td>
<td>0.2</td>
<td>Barren or sparsely vegetated</td>
</tr>
<tr>
<td>98</td>
<td>39</td>
<td>0.2</td>
<td>Loblolly Pine, Longleaf Pine, Slash Pine, Shortleaf Pine</td>
</tr>
<tr>
<td>67</td>
<td>20</td>
<td>0.1</td>
<td>Greasewood, Sage</td>
</tr>
<tr>
<td>72</td>
<td>10</td>
<td>0.1</td>
<td>Greasewood, Sage, Rabbitbrush, Needlegrass</td>
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<tr>
<td>34</td>
<td>5</td>
<td>0.0</td>
<td>Irrigated Agriculture, Mixed row crops</td>
</tr>
<tr>
<td>35</td>
<td>5</td>
<td>0.0</td>
<td>Bluestem, Grama, Wheatgrass, Small Grains</td>
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<td>12</td>
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<td>1</td>
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<td>0.0</td>
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<td>130</td>
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<td>0.0</td>
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<td>40</td>
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<td>0.0</td>
<td>Riparian Woods, Irrigated Agriculture, Blue Grama</td>
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<tr>
<td>74</td>
<td>1</td>
<td>0.0</td>
<td>Big Sage, Rabbitbrush, Wheatgrass, Fescue</td>
</tr>
</tbody>
</table>
Table 3: Making of 10 new associations from the 36 associations listed in table 1. The class numbers that were put together to make the new associations are also given.

<table>
<thead>
<tr>
<th>New Biomes</th>
<th>Classes joined together</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>20, 36, 34, 12, 1</td>
</tr>
<tr>
<td>Alpine Forest</td>
<td>98</td>
</tr>
<tr>
<td>Conifer Forest</td>
<td>129, 118, 108, 111, 115, 130</td>
</tr>
<tr>
<td>Creosote-Mesquite</td>
<td>68</td>
</tr>
<tr>
<td>Desert Grassland</td>
<td>82, 58, 83, 80, 35</td>
</tr>
<tr>
<td>Oak_Grass</td>
<td>88, 89, 40</td>
</tr>
<tr>
<td>Dry Playa</td>
<td>155</td>
</tr>
<tr>
<td>Sage-Creosote</td>
<td>77, 73, 69, 79</td>
</tr>
<tr>
<td>Sage-Grass</td>
<td>76, 81, 70, 71, 66, 127, 74</td>
</tr>
<tr>
<td>Sage-Oak</td>
<td>75, 67, 72</td>
</tr>
</tbody>
</table>
TABLE 4. Flux values form METFLUX sites and model outputs. ST stands for sites, LH means Lucky hills, KN means Kendall, M and F imply modeled and METFLUX values respectively. All the flux values are in W/m$^2$

<table>
<thead>
<tr>
<th>DOY</th>
<th>ST</th>
<th>Rn(F)</th>
<th>Rn(M)</th>
<th>G(F)</th>
<th>G(M)</th>
<th>H(F)</th>
<th>H(M)</th>
<th>LE(F)</th>
<th>LE(M)</th>
</tr>
</thead>
<tbody>
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Figure captions:

Figure 1: Sketch of the study area, along with the positions of weather stations. Walnut gulch is the triangular filled area in the lower half of the study area. Kendall and Lucky hills were located inside this watershed.

Figure 2: Biome map of the study area. Ten different biomes were identified in the area. Legends of the biomes are expressed in respective colors.

Figure 3: Spatial extrapolation of air temperature based on lapse rate and DEM. Top figure is that of air temperature at sea level, bottom one is that of DEM, and the middle one is the adjusted air temperature of the area. This figure represents air temperature of DOY 162. Air temperature for other DOYs were derived similarly.

Figure 4: Comparison of modeled and measured fluxes at Kendall and Lucky hills combined. Eight points in these graphs comprise of four DOYS in two subwatersheds (namely Kendall and Lucky hills). Respective fluxes and their MAD values are mentioned in each graph. The straight lines in the graphs are 1:1 lines.

Figure 5: LE flux from different biomes of the region for all four days. Playa always has the lowest LE. Forest generally has the highest LE, except in DOY 178. Also noticeable is that the LE flux in DOY 162 was relatively higher than that in all other DOYs in all biomes except agriculture.

Figure 6: LE map of the area. Top one (A) is that of DOY 162. Bottom one (B) is of DOY 178. DOY 162 had a high LE almost all over the area except in agriculture (the black spots in the middle of the map).

Figure 6: LE map for the area. Top one (C) is that of DOY 274 and bottom one (D) is that of DOY 306. Values of LE for all four DOYs are in W/m². Higher LE values in riparian and mountain areas are apparent.
Figure 1
Gridded temperature (C) at sea level

DEM adjusted air temperature (C)

DEM @ 1.1 km mesh

Figure 3
Figure 4
Figure 6
Figure 6
APPENDIX B:

On The Use of Mid-Morning Remotely Sensed and Ground-Based Data to Estimate Daily Evapotranspiration

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Abstract

Two simple semi-empirical models of estimating daily evapotranspiration were tested using mid-morning remotely sensed data. These models (named as ‘Seguin-Itier’ and ‘Jackson’ models) were previously tested using mid-day NOAA-AVHRR data and they were found to produce good estimation of daily evapotranspiration. The present paper tests the usability of these models when mid-morning remotely sensed data are used. It was found that the ‘Seguin-Itier’ model needs some modification to be used with mid-morning data. Jackson model was found to be useable with mid-morning data without any modification. Jackson model produced a MAD of 0.59 and Seguin-Itier model produced a MAD of 1.79 (both in the range of -0.5 to 11.6 mm/day of measured daily evapotranspiration) when the model outputs were compared with measured daily evapotranspiration data.
1. Introduction

Efforts have been made in recent years to estimate daily evapotranspiration \((ET_d)\) of an area using remote sensing. Since remotely sensed measurements are made periodically and are essentially instantaneous in nature, it is naturally a problem to convert 'one time of day' measurements to daily integrated values. Simple semi-empirical models have been proposed in the past (Seguin and Itier, 1983; Jackson et al., 1983) to relate instantaneous evapotranspiration \((ET_i)\) to \(ET_d\). Mid-day remotely sensed data from NOAA-AVHRR were used to validate those models. Since a wealth of mid-morning remotely sensed data exist from LANDSAT satellites and since most of the future EOS satellites will have a mid-morning overpass time, it is of interest to see if the mid-morning remotely sensed data can be used with those semi-empirical models to estimate \(ET_d\) of an area.

2. Theory

Remotely sensed data can be used to estimate instantaneous evapotranspiration \((ET_i)\) as a residual from the surface energy balance equation (Moran et al., 1989), which can be expressed using the relation:

\[
ET_i = Rn_i - H_i - G_i
\]  

(1)

where \(Rn_i\) stands for instantaneous net radiation flux, \(H_i\) for instantaneous sensible heat flux and \(G_i\) for instantaneous soil heat flux (all in units of mm/s).
On a daily basis, the soil heat flux $G$ can be neglected and the equation (1) can be rewritten as

\[ ET_d = Rn_d - H_d \]  \hspace{1cm} (2)

where the subscript \(d\) stands for daily integrated values (and the subscript \(i\) stands for instantaneous values; these are used as such for the rest of this paper). All the daily values are in units of mm/day.

Several simplified techniques have been proposed and several models have been tested in the past years to achieve the goal of estimating $ET_d$ values from one time measurements of surface and atmospheric parameters. The basic idea behind these approaches consisted of relating daily evapotranspiration to some easily measurable factors such as solar radiation, net radiation, surface temperature and air temperature etc.

Seguin and Itier (1983) have tested a model originally proposed by Jackson et. al. (1977),

\[ ET_d = Rn_d - B(T_s - T_a) \]  \hspace{1cm} (3)

where $T_s$ and $T_a$ are instantaneous surface temperature and air temperature ($^\circ C$) respectively, and $B$ is the "mean exchange coefficient" used for conversion from instantaneous to daily values. Seguin and Itier (1983) presented a detailed discussion of the $B$ factor concerning its theoretical basis and practicability of application. The formulation for $B$ is as follows:
\[ B = \left( \frac{R_{nd}}{R_{ni}} \right) C_v h_i \]  

where \( C_v \) is the volumetric heat capacity of air and \( h_i \) is the exchange coefficient of \( T_a \) at height \( z \) of measurement. Within limits of a first order approximation and for neutral conditions \( (T_s = T_a) \), the exchange coefficient \( h_i \) can be written as:

\[ h_i = \left( k \frac{2}{\log(z/z_o)} \right)^2 U \]

where \( k \) is the von Karman constant \((= 0.4)\), \( U \) is the wind speed at height \( z \), and \( z_o \) is the roughness parameter (Kustas et al., 1994).

Seguin and Itier used the mid-day (1300 - 1400h) values of \( T_s \) and \( T_a \) to test the model. The \( R_{nd} \) value was based on following assumptions:

\[ \frac{R_{nd}}{R_{ni}} = 0.3 \pm 0.03 \]  

and,

\[ \frac{H_d}{R_{nd}} = \frac{H_i}{R_{ni}} \]

All the daily values are in mm/day and the instantaneous values correspond to mid-day data. Based on these assumptions and the evaluation of inputs to equation (5), Seguin and Itier (1983) found the values of \( B \) to be 0.25 for unstable conditions and 0.18 for stable conditions. The authors also found that these assumptions resulted in a good estimation of \( ET_d \) over the irrigated and dry crop fields of Crau plain in France. The limitation of this approach, as pointed out by the authors, is that large variations in \( B \)
value may arise based on the $z_a$ and $U$ values for any given day and they cautioned that this procedure of $ET_d$ estimation must be applied to long term periods (at least several weeks) so that daily extremes are damped and the mean values of $B$ can be used with confidence.

Jackson et. al. (1983) proposed another simple technique of estimating $ET_d$ using a mid-day $ET_i$ value and a 'J' factor, where

$$J = S_d / S_i$$

and $S$ is the incoming solar radiation. Values of $S_i$ and $ET_i$ were measured at mid-day. According to this model, $ET_d$ can be estimated as follows:

$$ET_d = J(ET_i)$$

The authors obtained reliable estimates of $ET_d$ on wheat using this model. They also suggested that since the 'J' factor can be readily calculated for the cloud free days knowing the latitude, time of day and day of year, this model can be useful in estimating regional-scale $ET_d$ from $ET_i$. Thus, the authors concluded that this procedure of $ET_d$ estimation can be used with the models which estimate $ET_i$ from remotely sensed measurements (Jackson et. al., 1987; Moran and Jackson., 1991). The limitations of this procedure is that it assumes invariant wind and cloud conditions over the day, which is not the case for real life situations. Also the errors in estimation of $ET_i$ would lead to erroneous results for daily values.
3. Objective

Both of the above-mentioned models (equations (3) and (9)) were originally tested by the scientists (Seguin and Itier, and Jackson et al., respectively) using mid-day (1300h-1400h LST) data to estimate the daily values. This was due to the fact that scientists used NOAA-AVHRR as a source of remotely sensed data, and NOAA overpass is in the early afternoon (~2:00 PM LST). So the model developments and verifications were made using remotely sensed data and auxiliary ground data collected at mid-day. Less attention was paid to the mid-morning data (at around 10:15 AM LST) from LANDSAT satellites even though a lot of data have been collected by these satellites over last two decades. Since the spatial resolution of LANDSAT satellites is higher than that of NOAA and the future EOS satellites will have a similar mid-morning overpass time, it is of interest to examine if these models can utilize mid-morning remotely sensed data to estimate $ET_d$ of a region.

Lagouarde (1993) has examined some aspects of mid-morning remotely sensed surface temperature, such as effect of surface roughness and sensitivity to the time of acquisition etc. His study shows that the values of surface temperature at mid-morning and at mid-day are closely related in all clear sky cases. Also, the author noted that roughness length variation did not have any significant impact on the $(T_s - T_a)$ values from either mid-morning or mid-day. In conclusion, the author pointed out the interest of the mid-morning $T_s$ and $T_a$ for water budget monitoring studies.
The objective of the present study was to test the usability of mid-morning remotely sensed data for the estimation of $ET_d$. Relationships stated in equations (6) and (7), and the stability of the relation stated in equation (8) were tested using mid morning data. The reason for testing these relationships (equations 6, 7 and 8) was to see if the parameters $B$ and $J$ can be used with the mid morning data. These results were then used to estimate $ET_d$ using both of the above-mentioned approaches (i.e., Seguin-Itier and Jackson). Hereon, the model used by Seguin and Itier (1983) will be termed as ‘Seguin-Itier’ model and that by Jackson et al. (1983) will be termed as ‘Jackson’ model.

4. Data

In 1992, an experiment, termed ‘WG92’ was conducted in Walnut Gulch watershed near Tombstone, Arizona. Measurements of net radiation, solar radiation and air temperature were collected and averaged at hourly intervals using the METFLUX stations (see Stannard et. al, 1994) from Kendall and Lucky Hills subwatersheds inside the Walnut Gulch watershed. Kendall was a hilly, grass-dominated region and Lucky Hills was a shrub-dominated, relatively flat area. A detailed description of this watershed is given by Kustas et al. (1994). Surface temperature data of these two sites were derived from TM band 6 Digital Counts (DC) of LANDSAT-5 satellite image of the area. The procedure used for the derivation of surface temperature from TM satellite image is described in details by Washburne (1994). Clear sky and unstable conditions prevailed on both sites during the satellite overpass time in all four above-mentioned days. Thus, the satellite $T_s$ and METFLUX $R_n$, $H_i$, and $S_i$, data from Kendall and Lucky Hills,
collected on four days in 1992, namely DOYs (day of year) 162, 178, 274 and 306, were used to test if the equations (6), (7) and (8) of this paper hold good when mid-morning data are used. Then the values of $Rn_d$ and instantaneous values of $T_s$ and $T_a$ (at 10:00 - 11:00 AM LST interval) from the METFLUX stations in Kendall and Lucky Hills for 112 days (ranging from DOY 226 to DOY 365) of 1992 were used to compare the results of ‘Seguin-Itier’ $ET_d$ with METFLUX $ET_d$. Values of $ET_i$ (at 10:00 - 11:00 AM LST interval) from METFLUX stations at Kendall and Lucky Hills for the same 112 days in 1992 were used to validate the ‘Jackson’ model.

5. Model validation with mid-morning data

As mentioned in the ‘objectives’ section, the utility of equations (6) and (7) were tested using the mid-morning data. The relation $Rn_d/Rn_i$ (equation (6)) from sunrise to sunset for the four days in the two subwatersheds is shown in figure 1. It is clear that mid-morning (10:15 AM) values were slightly higher than the values at noon. But the values were also found to vary from DOY to DOY. Values on DOYs 162 and 178 were higher than those measured on DOYs 274 and 306. Also the proposed value for this relation (0.3± 0.03, as in equation (6)) did not fit the noon values measured at Kendall and Lucky Hills. Early morning or mid afternoon values fit the given range of the relation. It can be suggested from the figure that for the present paper, the mid-morning value of $Rn_d/Rn_i$ relation can be taken to be ≈0.3 for DOYs 162 and 178, and ≈0.2 for DOYs 274 and 306. As shown by Jackson et al. (1983), probable reason of this variation is that the ratio of $S_d/S_i$ varies not only with time of day but significantly with DOY also
(Figures 1 and 2 in their paper). Since solar radiation is a prominent factor in determining $R_{ni}$, and hence $R_{nd}$ also; the $R_{nd}/R_{ni}$ ratio also varies based on DOY.

The $H_i/R_{ni}$ relation from sunrise to sunset is shown in figure 2. For both subwatersheds in four days, the relationship was not constant on any given day; the ratio increased with the time of the day. Except for 3 data points on DOY 306 at Lucky hills (corresponding to times 1300-1500h), the relationship showed a linear increase with time of day in both subwatersheds. So, the assumption that this relation had a constant value (for a given day) equal to $H_d/R_{nd}$ was not the case in the present study. The instantaneous values of $H_i/R_{ni}$ approached the daily values of $H_d/R_{nd}$ in the early afternoon time (13:00 - 14:00h).

A comparison between $H_d/R_{nd}$ and $H_i/R_{ni}$ for the four days at Kendall and Lucky hills is shown in figure 3. It is clear that the two ratios were not equal. The MAD between these two sets of ratios ($H_d/R_{nd}$ and $H_i/R_{ni}$) was 0.173. In fact, the $H_i/R_{ni}$ ratio linearly increased from almost 0.0 to 1.0 over a time span of 12 hours (5:00 - 17:00h) (figure 2). So an hourly adjustment of 0.08 (1/12) with $H_d/R_{nd}$ can be suggested for this relation (as in equation (7)) to be useful in any time other than the 13:00 - 14:00h interval. Hence equation (7) for a given hourly interval can be rewritten as:

$$H_d / R_{nd} = H_i / R_{ni} - f \Delta t$$

where $f$ is the adjustment factor 0.08 and $\Delta t$ is the difference in number of hourly intervals between the observation time and the interval of 13:00 - 14:00h. $\Delta t$ is a
dimensionless integer only, and will have its sign positive if it is above 14:00h and negative if below 13:00h. A comparison between METFLUX $H_d/Rn_d$ and the adjusted values of $H_d/Rn_d$ from equation (10) will be shown later.

Rearranging equation (10), the following relation can be easily derived:

$$H_d = Rn_d H_i / Rn_i - f\Delta t Rn_d$$

and using this relation in equation (8) of Seguin and Itier (1983) leads to the rewriting of equation (3) of this paper as follows:

$$ET_d = Rn_d (1 - f\Delta t) - B (T_s - T_a)$$

which includes the adjustment mentioned in equation (10). In 1300 - 1400h interval equation (12) will take the form of equation (3).

The relation between METFLUX values of $(ET_d - Rn_d)$ and $(T_s - T_a)$, for the two subwatersheds together and also the value of regression coefficient (which is statistically equivalent to $B$ from equation (3)) between these two terms are plotted in figure 4. The intercept was forced to go through zero and the regression coefficient ($=B$) was found to be 0.26, which is close to the $B$ value for unstable condition (0.25) proposed in ‘Seguin-Itier’ model.

Thus, equation (12) can be used for the purpose of $ET_d$ estimation using mid-morning remotely sensed and ground-based data. Also the relation between $H_i/Rn_i$ and
\( H_d / Rn_d \) for mid-morning instantaneous values can be tested using equation (10). The result of using equations (10) and (12) will be discussed in the next section.

The \( S_d / S_l \) ratio (both measured with instrumentation on the METFLUX sites) over sunrise to sunset for Kendall and Lucky Hills are plotted in figure 5. Even though there was tendency for variation in the values based on DOY, the values were almost the same at 10:15 and 13:30 (middle of 1300 - 1400h). It can probably be deduced that equation (8) holds for mid-morning as well as afternoon \( J \) factor estimation, and equation (9) can be used to estimate the \( ET_d \) values using mid-morning data.

6. Model performance statistics and discussion

This section describes the statistical methods and inferences used in this study to identify the performance of the two models (modified ‘Seguin-Itier’ and ‘Jackson’) in comparison to the METFLUX estimates of \( ET_d \). Although Pearson’s Product-Moment Correlation Coefficient \( (r) \), the coefficient of determination \( (R^2) \), and tests of their significance are commonly used in the literature for determining model performance, Willmott (1981) demonstrated that they are inadequate for this purpose. To satisfy this function, he recommended an alternative set of indices for comparing predicted and observed values, including mean absolute difference \( (MAD) \), root mean square error \( (RMSE) \) and Willmott’s index of agreement \( (d) \).

\( MAD \) and \( RMSE \) estimate the average error and take the form:
\[ \text{MAD} = \frac{1}{N} \sum_{i=1}^{N} |P_i - O_i| \]  

and

\[ \text{RMSE} = \left[ \frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)^2 \right]^{0.5} \]

where \( O \) and \( P \) are the observed (METFLUX) and model-predicted values respectively, and \( N \) is the number of observations.

Wilmott’s index of agreement, \( d \), reflects the relative degree to which predicted values approach observed values.

\[ d = 1 - \frac{N(RMSE)^2}{PE} \]

where the potential error variance \( (PE) \) is:

\[ PE = \sum_{i=1}^{N} \left[ |P_i| + |O_i| \right]^2 \]

\( d \) varies between 0.0 and 1.0, with 1.0 expressing perfect agreement between observed and predicted values and 0.0 describing complete disagreement. The specialty of this index is that there is no absolute value that its magnitude must reach to become “significant” (Yarnal, 1993). Instead, the investigator must evaluate the import of the \( d \)-score on the basis of his or her knowledge about the phenomenon being studied, the
data's accuracy, and the models being employed. The index of agreement is only meaningful in the context of the problem under investigation.

The comparison between $H_d/Rn_d$ values observed from METFLUX stations and $H_d/Rn_d$ obtained by using equation (10) is shown in figure 6. The MAD between the two sets of values was 0.07. This is an improvement from the result shown in figure 3 (MAD was 0.173).

The results of using equations (9) and (12) with data from Kendall and Lucky Hills for four DOYs are plotted in figure 7. Equation (12) produced a larger scatter around the 1:1 line. In that respect, equation (9) produced a slightly better estimate of $ET_d$. Results of statistical analyses of the outputs from both models are shown in Table 1. Values of the $ET_d$ from both models, as well as the data used for the present study, are shown in Table 2.

Table 1 shows that Jackson model had lower MAD and RMSE values than Seguin-Itier model for the four DOYs. The $d$ statistic was higher for results using the Jackson model. Previous works with the flux data from the same sites and their small values lead to a suggestion that the range of $d$ using the present data can be 0.9 to 1.0, indicating that a value above 0.95 is better than a value lower than 0.95. For these data and these models, a $d$ value of 0.9 would be associated with relatively poor results. In that light the Jackson model had a marginally better performance ($d = 0.96$) than Seguin-Itier model ($d = 0.93$). Errors in Seguin-Itier model might be from inaccurate $T_s$ estimation using remote sensing. The possible errors in the Jackson model might be due
to errors in the estimation of $ET_i$. As Moran et al. (1994) and Rahman (1993) have shown for data collected from the same study area, the remote estimation of $ET_i$ can have a 25-52% error induced in it due to the accumulated error in the procedure of its estimation.

The comparison between METFLUX and modeled $ET_d$, using equations (9) and (12) with the 112-days data are shown in figure 8. This was done to see the effectiveness of modified Seguin-Itier and Jackson models when the parameters were correctly estimated. As can be seen from the figure, the Jackson model showed a better performance than the modified Seguin-Itier model. The Jackson model output had a MAD of 0.59 and modified Seguin-Itier model output had a MAD of 1.79, both in the range of -0.5 to 11.6 mm/day of measured $ET_d$ (from METFLUX stations). Also the modified Seguin-Itier model had a tendency to overestimate the $ET_d$ as the values go higher. The Jackson model showed a tighter fit around the 1:1 line than the modified Seguin-Itier model.

When taken together, the model performance statistics show that Jackson model had a little higher rating than the modified Seguin-Itier model in estimating $ET_d$ using mid-morning data. Also, Jackson model has some other advantages to consider. The 'J' factor should be generally stable in a regional scale in clear sky condition. It also should be free of surface variations, which $Rn_i$ is not (used in Seguin-Itier model). But this study does not include the variable cloudy conditions, which is the reality most of the time in most of the places. Also most of the present models for estimating $ET_i$ using remotely
sensed data produce errors and this is a big drawback for application of this method. If some reliable models can be developed to correctly estimate regional-scale $ET_i$ of a heterogeneous terrain using remotely sensed and minimum ground-based data, that will make this approach more suitable to apply over a heterogeneous region.

In the present study, the modified Seguin-Itier model produced fairly good estimation of $ET_d$ over rangelands. But the equations (6) and (7) and also the value of $B$ factor need yet to be verified over forests, dry lakebeds, riparian vegetation etc., thus limiting the use of it only on rangelands (or agriculture in case of Seguin and Itier, 1983). Computations of $B$ over different kinds of vegetation can expand the usability of this model.

7. Conclusion

Considering these statistical performances and model usability, it can probably be safely concluded that both the modified Seguin-Itier and Jackson models have advantages and disadvantages. When remote sensing was used operationally, both models were equally error prone due to inaccuracy in $T_s$ and $ET_i$ estimation using remote sensing approach. Using the 112 days data from METFLUX stations, Jackson model worked slightly better for Kendall and Lucky Hills. In any case, it was apparent that both models can be used with mid-morning data, though care should be taken so that in case of Jackson model, remotely sensed data are collected in cloud-free conditions and error associated with $ET_i$ estimation are known. In case of modified Seguin-Itier model, the $B$ values for various biome should be previously estimated and also the error associated
with remotely sensed $T_s$ should be known. If these factors are taken care of, any of these models might be used for estimation of $ET_d$ using 'one-time of a day' data acquired at mid-morning.
Table 1: Model performance statistics for the Seguin-Itier and Jackson models using data from four days of the year 1992.

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<th>Jackson model</th>
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Table 2: Values of the model parameters used in the analyses, and model outputs of the present study (for four DOYs). Top one is for Kendall and bottom one for Lucky hills. DOY stands for Day Of Year. $T_s$ and $T_a$ are in degree Centigrade. Everything else is in mm/day. ‘Est’ stands for estimated and ‘Flux’ stands for METFLUX data. ‘S-I’ is for modified ‘Seguin-Itier’ model output and ‘Jack’ is for that of Jackson model.

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Figure 1: The ratio of $R_{nd}/R_{ni}$ over time of day (from 6:00 to 18:00). The top figure (A) is for Kendall and the bottom one (B) is for Lucky hills. In both cases horizontal solid line and dashed lines mean the range $0.3 \pm 0.03$ for both figures.

Figure 2: Ratio of $H_{i}/R_{ni}$ over time of day. Top figure (A) is for Kendall and bottom one (B) is for Lucky hills.

Figure 3: Comparison between $H_{i}/R_{ni}$ at 10:15 AM and $H_{d}/R_{nd}$, both from METFLUX stations, for Kendall and Lucky hills, showing very little agreement (MAD 0.173).

Figure 4: Relationship between $(T_{s} - T_{a})$ and $(ET_{d} - R_{nd})$ using data from four DOYs in 1992 from Kendall and Lucky Hills. The regression coefficient, which is equivalent to B value in equation (3) of the present paper, was 0.26 when the regression line was forced to go through zero.

Figure 5: Ratio of $S_{d}/S_{i}$ over time of day for Kendall (A) and Lucky hills (B). Values are similar at mid-mornings and at mid-days.

Figure 6: Comparison between METFLUX $H_{d}/R_{nd}$ and adjusted values of $H_{d}/R_{nd}$ for Kendall and Lucky hills. It shows a better agreement than shown in figure 3. MAD was 0.173 in figure 3, here MAD is 0.07.
Figure 7: Verification of Seguin-Itier and Jackson model output with METFLUX estimates of ET_d for four days in Kendall and Lucky Hills. Jackson model shows a slightly better performance with a MAD of 0.51 than Seguin-Itier model with a MAD of 0.63 in a range of 0.5 to 2.5 mm/day of METFLUX ET_d.

Figure 8: Comparison between modeled and estimated ET_d values using the METFLUX values of Ts, Ta and ETi in the model estimation. Seguin-Itier model overestimates the measurements and have a MAD of 1.79. Jackson model has a tighter fit around the 1:1 line and have a MAD of 0.59.
Figure 1
Figure 2
Figure 3
Figure 4
Figure 5

Kendall Site

Lucky Hills Site
Figure 6
Figure 7
Figure 8
Dear Dr. Kiebert,

I am a graduate student at the University of Arizona. My name is Abdullah Faizur Rahman. I am interested, and requesting your written permission, to reproduce the following article in my Ph.D. dissertation:

Combining the Penman-Monteith equation with measurements of surface temperature and reflectance to estimate evaporation rates of semiarid grassland (1996, 80:87-109).

My dissertation director Dr. M. S. Moran (the first author of the article, I am-the second author) has agreed that I should include this paper in my dissertation. I am sending a copy of this mail to her also. In response to my email earlier, Dr. D. E. Aylor (Editor-in-Chief) suggested that I should write to you for this purpose. I am including his mail at the end of this mail.

I plan to complete my Ph.D. requirements by next month (Nov '96). It would be very helpful for me if you kindly give me the permission and send me a written reply at the following address:

Abdullah F. Rahman
Dept. of Soil and Water science
Shantz Building, Room # 429
University of Arizona
Tucson, AZ 85721

Phone: (520)621-9187

I appreciate your help in this regard.

Sincerely yours,
Abdullah F. Rahman

*******************************************************************************
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429 Shantz Building, 438
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Tucson, AZ 85721
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Direct Fax : (20) 4852 722

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Combining the Penman–Monteith equation with measurements of surface temperature and reflectance to estimate evaporation rates of semiarid grassland

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Received 25 July 1995; accepted 26 July 1995
Combining the Penman–Monteith equation with measurements of surface temperature and reflectance to estimate evaporation rates of semiarid grassland

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Abstract

The Penman–Monteith equation is useful for computing evaporation rates of uniform surfaces, such as dense vegetation or bare soil. This equation becomes less useful for evaluation of evaporation rates at the regional scale, where surfaces are generally characterized by a patchy combination of vegetation and soil. This is particularly true in the arid and semi-arid regions of the world. The approach proposed here is an attempt to use remotely-sensed measurements of surface reflectance and temperature to allow application of the Penman–Monteith theory to partially-vegetated fields without a-priori knowledge of the percent vegetation cover and canopy resistance. Basically, the Penman–Monteith equation was combined with the energy balance equation to estimate the surface temperature \( T_s \) associated with four states: surfaces characterized by full-cover vegetation and bare soil with evaporation rates at potential and zero. Then, linear interpolations between \( T_s \) values computed for full-cover and bare soil conditions were used to provide information at intermediate states based on measurements of actual surface reflectance and temperature. The approach was first tested using ground-based measurements of surface reflectance and temperature at a rangeland site: the results compared well with on-site measure-

* Corresponding author.
ments of surface evaporation rate (RMSE = 29 W m\(^{-2}\)). Then, the approach was tested based on a set of four Landsat Thematic Mapper (TM) images acquired in southeast Arizona during 1992. Maps of surface air temperature and wind speed were combined with maps of surface temperature and spectral vegetation index to produce regional estimates of evaporation rates for the grassland biome.

1. Introduction

The Penman–Monteith (P–M) equation is well-known for estimation of evaporation (\(E\)) and transpiration (\(I\)) rates from 'uniform' surfaces (Monteith, 1973; Allen, 1986). It requires knowledge of basic meteorological conditions such as vapor pressure deficit (VPD), air temperature (\(T_a\)) and wind speed (\(U\)), and estimates of canopy and aerodynamic resistances. The difficulty in measuring the latter two inputs for partially-vegetated sites generally limits application of the P–M equation to full-cover vegetation and bare soil. In fact, the most common application of the P–M equation is for estimation of potential \(I\) or \(E\) from full-cover vegetation or open-water surfaces. Unfortunately, for most resource monitoring/management applications, a value of actual evapotranspiration (\(E_T\)) rate is far more useful. Actual \(E_T\) has been used as a direct indicator of soil moisture content, soil water matrix potential, soil salinity, soil waterlogging, plant water potential, leaf diffusion resistance and photosynthesis, and even final crop yield.

In recent years, there has been a great deal of study to use remotely sensed data to estimate actual \(E_T\). One avenue that has proven particularly successful has been the incorporation of remotely sensed spectral measurements with ground-based meteorological measurements in the P–M equation. The link between the P–M equation and remotely sensed measurements of surface temperature was first made by Jackson et al. (1981). They combined the P–M equation with a one-dimensional energy balance equation to allow estimation of the maximum and minimum foliage temperatures (\(T_{cx}\), \(T_{cm}\), where subscript 'c' refers to canopy foliage temperature and subscripts 'x' and 'm' refer to maximum and minimum temperatures, respectively) associated with instantaneous minimum and maximum transpiration rates, respectively. Then, by comparison of these extreme foliage temperatures with a measurement of actual foliage temperature, it was possible to estimate the ratio of actual to potential \(E_T\) and infer plant water stress.

Based on this theory, they developed the Crop Water Stress Index (CWSI) which has since been used extensively for such important farm applications as irrigation scheduling, predicting crop yields, and detecting certain plant diseases. Because CWSI requires a measurement of foliage temperature and because most airborne and satellite-based sensors measure composite surface temperature (\(T_s\): a composite of soil and vegetation temperatures), application has generally been limited to fully-vegetated sites, such as agricultural fields.

Moran et al. (1994a) suggested that CWSI could be refined for application to partially-vegetated surfaces by including measurements of surface reflectance in addition to surface temperature. Based on the P–M equation, they computed the maximum and minimum soil temperatures (\(T_{ox}\), \(T_{om}\), where subscript 'o' refers to soil temperature) associated with minimum and maximum evaporation rates, respectively. These four
temperatures \((T_c, T_m, T_{ox}, T_{om})\)\(^1\) were plotted against a spectral vegetation index (which is linearly correlated with percent vegetation cover; see Huete and Jackson, 1988; Huete, 1988; Moran et al., 1994b) to form a trapezoidal shape that encompassed all possible values of surface temperature for both full-cover and partially-vegetated surfaces (Fig. 1). With a measurement of \(T_s\) at point C, it was possible to equate the ratio of actual to potential evapotranspiration with the ratio of distances CB and AB. They defined this ratio as the Water Deficit Index (WDI).

Moran et al. (1994a) gave a theoretical justification (with assumptions and limitations) and experimental demonstration of the WDI for agricultural applications at the field scale. The work presented here is an attempt to apply this theory to semiarid grassland vegetation at the local and regional scale. The goal was to test this operational technique for monitoring changes in surface conditions for applications in regional resource management. As such, we used data from existing meteorological stations and the currently-orbiting Landsat Thematic Mapper (TM). At the local scale, modeled evaporation rates were compared with ground-based measurements at one site; at the regional scale, the modeled evaporation rates for the entire grassland biome were validated with knowledge of recent rainfall events and on-site meteorological conditions. The potential for use in other biomes was also demonstrated.

\(^1\)It is important at this point to emphasize the differences between \(T_c\), \(T_o\) and \(T_s\). \(T_c\) is the foliage or ‘crop’ temperature; \(T_o\) is the temperature of the soil surface; \(T_s\) is the surface composite temperature; that is, a weighted average of soil and vegetation temperatures. When the surface is completely covered by vegetation, then \(T_s = T_c\); and when the surface is bare soil, then \(T_s = T_o\). Throughout this discussion, all temperatures are assumed to be kinetic values; that is, all radiometric temperature measurements have been corrected for surface emissivity.
2. Background

In numerous studies, the observed negative correlation between surface temperature and spectral vegetation indices (such as Normalized Difference VI (NDVI) and Soil-Adjusted VI (SAVI)) has been related to plant transpiration and soil evaporation. That is, differences in the amount of vegetation, the leaf transpiration rate, and the soil evaporation rate result in variability in surface temperature measurements due to evaporative cooling. For dense vegetation with a complete canopy, the slope of the $T_s/NDVI$ relation has been related to canopy resistance (Sellers, 1987; Hope, 1988; Nemani and Running, 1989). For land surfaces with fractional vegetation cover, Nemani et al. (1993) found that the slope of the $T_s/NDVI$ relation was negatively correlated to a crop-moisture index. These relations have been corroborated by other empirical studies using a variety of sensors at different locations (Goward and Hope, 1989; Hope and McDowell, 1992). Though empirical relations such as these are useful for many applications, they require that the image cover the entire range of vegetation cover to supply sufficient information for computation of the $T_s/NDVI$ slope from the data. Furthermore, they do not work well when the soil moisture of partially-vegetated surfaces is spatially variable within the image, causing considerable scatter in the $T_s/NDVI$ relation. In response to these problems, attempts have been made to incorporate meteorological models with observations of $T_s$ and NDVI to improve estimates of surface conditions over partially-vegetated sites.

Price (1990) used energy balance theory to map regional evaporation rates. He estimated evaporation rates directly from the spatial variations in satellite-derived surface temperature and NDVI. Similarly, Carlson et al. (1990) and Carlson et al. (1994) combined a boundary layer model with vegetation and substrate components with $T_s$ and NDVI measurements to map soil moisture in the surface and root zone over patchy vegetation. Though this was an improvement over strictly empirical approaches, the model still required knowledge of the slope of the $T_s/NDVI$ relation derived from the image data. In refinement of this approach, Gillies et al. (1995) used a Soil-Atmosphere-Vegetation (SVAT) model to produce isolines of $T_s/NDVI$ data corresponding to a variety of surface moisture availability values. These lines were shifted to fit the range of data in the $T_s/NDVI$ scattergram, preserving the basic shape and non-linear spacing. Then, the new isolines were used to convert the $T_s/NDVI$ data to soil moisture availability values and the SVAT model was again run for each pixel value to map evaporation rates. Though this circumvented the need to derive the slope of the $T_s/NDVI$ relation, it was still dependent upon the scatter of the image data. As in the work of Price (1990), the methods of Carlson et al. (1990), Carlson et al. (1994) and Gillies et al. (1995) required spatial variability in the satellite data and did not apply in uniform areas.

Friedl and Davis (1994) used a soil-canopy-sensor (SCS) model and data from the First ISLSCP Field Experiment (FIFE) to conduct a comprehensive study of the land surface properties and processes that produce the distinctive relation between $T_s$ and NDVI. This work was conducted with the hope of exploiting this relation in strategies to model land surface energy balance from satellites. They reported that the observed covariance between $T_s$ and NDVI was due to temperature differences between the soil...
and vegetation and variations in fractional vegetation cover. Furthermore, they found the \( T_\text{c}/\text{NDVI} \) relation to be highly date and time specific, and dependent on land cover class. Based on these findings, they suggested that future work should be directed toward incorporating information on soil moisture in invertible surface energy balance models for regional applications.

The approach proposed by Moran et al. (1994a) addresses some of the issues identified by Friedl and Davis (1994). The technique utilized the P–M equation to define the theoretical boundaries of the \( T_\text{c} - T_\text{s}/\text{SAVI} \) relation based on date- and time-specific meteorological data, and reasonable values of vegetation and soil characteristics. Information about \( EI' \) rates was derived from the location of the \( T_\text{c} - T_\text{s} \) and SAVI measurements within the date- and time-specific trapezoid (Fig. 1). This avoided the reliance on empirical interpretation of the \( T_\text{c}/\text{SAVI} \) image scatter, and allowed application of the method to both heterogeneous and uniform areas, regardless of date and time. Moran et al. (1994a) limited their application to irrigated agricultural fields, with emphasis on applications in irrigation scheduling. Thus, it was unclear if the underlying assumptions and inputs were suitable for other important land cover classes, such as rangeland. This issue is the topic of the experiment and analysis presented here.

3. Theory

Jackson et al. (1981) combined the P–M equation with a one-dimensional energy balance equation to derive a computation for foliage-air temperature,

\[
(T_\text{c} - T_\text{s}) = \left[ r_\text{a}(R_n - G)/C_v \right] \left[ \gamma \left( 1 + \frac{r_\text{c}}{r_\text{a}} \right) / \left( \Delta + \gamma \left( 1 + \frac{r_\text{c}}{r_\text{a}} \right) \right) \right] - \left[ \text{VPD} / \left( \Delta + \gamma \left( 1 + \frac{r_\text{c}}{r_\text{a}} \right) \right) \right], \tag{1}
\]

where \( T_\text{c} \) is the crop foliage temperature (°C), \( T_\text{s} \) the air temperature (°C), \( r_\text{a} \) the aerodynamic resistance (s m\(^{-1}\)), \( R_n \) the net radiant heat flux density (W m\(^{-2}\)), \( G \) the soil heat flux density (W m\(^{-2}\)), \( C_v \) the volumetric heat capacity of air (J°C\(^{-1}\) m\(^{-3}\)), \( r_\text{c} \) the canopy resistance (s m\(^{-1}\)) to vapor transport, \( \gamma \) the psychrometric constant (Pa°C\(^{-1}\)), \( \Delta \) the slope of the saturated vapor pressure-temperature relation (Pa°C\(^{-1}\)), and \( \text{VPD} \) the vapor pressure deficit of the air (Pa). Eq. (1) was then solved for the ratio \( r_\text{c}/r_\text{a} \) which was used in the relation

\[
\text{CWSI} = 1 - \frac{r_\text{c}}{EIT_p} \left[ \gamma \left( 1 + \frac{r_\text{c}}{r_\text{a}} \right) - r_\text{c} \gamma \right] / \left( \Delta + \gamma \left( 1 + \frac{r_\text{c}}{r_\text{a}} \right) \right), \tag{2}
\]

where

\[
\frac{r_\text{c}}{r_\text{a}} = \frac{[\gamma r_\text{a} R_n / C_v] - [(T_\text{c} - T_\text{s})(\Delta + \gamma)] - \text{VPD}}{\gamma[(T_\text{c} - T_\text{s}) - r_\text{a}(R_n - G)/C_v]}. \tag{3}
\]
to obtain the ratio of transpiration $\Gamma$ to potential evapotranspiration $E\Gamma_p$.

Moran et al. (1994a) further developed this work to develop a new concept [termed Vegetation Index/Temperature (VIT) Trapezoid] which combined a spectral vegetation index with surface temperature measurements (a composite of both the soil and plant temperatures) to determine field water deficit conditions for partial cover crops. The spectral vegetation index used in this analysis was the Soil-Adjusted Vegetation Index (SAVI), where

$$\text{SAVI} = \frac{(\rho_{\text{NIR}} - \rho_{\text{red}})}{(\rho_{\text{NIR}} + \rho_{\text{red}} + L)(1 + L)},$$

and $\rho_{\text{NIR}}$ and $\rho_{\text{red}}$ are the near-IR and red reflectances, respectively, and $L$ is assumed to be 0.5 for a wide variety of leaf area index (LAI) values (Huete, 1988).

Eq. (1) was used to define the four vertices of a trapezoidal shape in a plot of surface-air temperature $(T_s - T_a)$ versus SAVI that encompassed all possible combinations of SAVI and $T_s - T_a$ for one vegetation type on one day. That is, for full-cover, well-watered vegetation,

$$(T_s - T_a)_1 = \left[ r_c (R_n - G)/C_v \right] \left[ \gamma (1 + r_{cp}/r_c) / \left( \Delta + \gamma (1 + r_{cp}/r_c) \right) \right]$$

$$- \left[ \text{VPD} / \left( \Delta + \gamma (1 + r_{cp}/r_c) \right) \right],$$

where $r_{cp}$ is the canopy resistance at potential evapotranspiration and the subscript 'n' of $(T_s - T_a)_n$ refers to vertex $n$ in Fig. 1. For full-cover vegetation with no available water,

$$(T_s - T_a)_2 = \left[ r_c (R_n - G)/C_v \right] \left[ \gamma (1 + r_{cx}/r_c) / \left( \Delta + \gamma (1 + r_{cx}/r_c) \right) \right]$$

$$- \left[ \text{VPD} / \left( \Delta + \gamma (1 + r_{cx}/r_c) \right) \right],$$

where $r_{cx}$ is the canopy resistance associated with nearly complete stomatal closure. For saturated bare soil, where $r_c = 0$ (the case of a free water surface),

$$(T_s - T_a)_3 = \left[ r_c (R_n - G)/C_v \right] \left[ \gamma / (\Delta + \gamma) \right] - \left[ \text{VPD} / (\Delta + \gamma) \right],$$

and for dry bare soil, where $r_c = \infty$ (analogous to complete stomatal closure),

$$(T_s - T_a)_4 = \left[ r_c (R_n - G)/C_v \right].$$

Monteith (1973) suggested the values of $r_{cp}$ and $r_{cx}$ could be obtained from measurements of stomatal resistance ($r_s$) and LAI, where

$$r_{cp} = r_s / \text{LAI} \text{ and } r_{cx} = r_s / \text{LAI},$$

where LAI > 0. Values of minimum and maximum stomatal resistance ($r_{sp}$ and $r_{sx}$, respectively) are published for many plant types under a variety of atmospheric conditions. If values are not available, reasonable values of $r_{sp} = 25-100$ s m$^{-1}$ and $r_{sx} = 1000-1500$ s m$^{-1}$ won't result in appreciable error.

The assumptions associated with the VIT Trapezoid warrant some discussion. First, the VIT Trapezoid is based on the premise that measurements of vegetation cover ($V_c$) are linearly related to SAVI. Second, one must assume that $T_s - T_a$ is a linear function of $V_c$, canopy-air temperature $(T_c - T_a)$ and soil-air temperature $(T_o - T_a)$, where

$$T_s - T_a = V_c (T_c - T_a) + (1 - V_c) (T_o - T_a).$$

(10)
This assumption allows straight lines to be drawn between points 2 and 4 and between points 1 and 3 in Fig. 1. A third assumption that links the VIT Trapezoid to crop water conditions is that, for a given $R_n$, VPD and $r_s$, variations in $T_c - T_a$ and $T_o - T_s$ are linearly associated with variations in evaporation ($E$) and transpiration ($\Gamma$). That is,

$$T_c - T_a = a + b(\Gamma)$$  \hspace{1cm} (11)

and

$$T_o - T_s = a' + b'(E),$$  \hspace{1cm} (12)

where $a$, $a'$, $b$ and $b'$ are semi-empirical coefficients. The above-mentioned assumptions were thoroughly addressed and justified by Moran et al. (1994a).

The relations presented in Eqs. (5)–(12) imply that variations in $T_c - T_a$ are associated with variations in evapotranspiration ($E\Gamma$). Thus, it follows that for a partially-vegetated surface,

$$\text{WDI} = 1 - \frac{E\Gamma}{E\Gamma_p} = \frac{[(T_c - T_a)_m - (T_c - T_a)_x]/[(T_c - T_a)_m - (T_c - T_a)_r]}{[(T_o - T_s)_m - (T_o - T_s)_x]/[(T_o - T_s)_m - (T_o - T_s)_r]},$$  \hspace{1cm} (13)

where WDI is the Water Deficit Index, $E\Gamma$ is the evapotranspiration rate of the surface, $E\Gamma_p$ is the potential evapotranspiration rate, and the subscripts 'm', 'x' and 'r' refer to the minimum, maximum and measured values, respectively. Graphically, WDI is equal to the ratio of distances AC/AB in Fig. 1. Thus, WDI = 0.0 for well-watered conditions and WDI = 1.0 for maximum stress conditions.

4. Experimental data

To test the WDI theory for regional application, data from an experiment, referred to as WG'92, was analyzed for a semiarid region in southeastern Arizona. The experimental site was chosen to encompass the USDA–ARS Walnut Gulch (WG) Experimental Watershed, which has been the location of prior hydrologic remote sensing experiments (Kustas and Goodrich, 1994) and contains extensive hydrologic instrumentation (Renard et al., 1993). WG'92 was conducted during the dry, early-monsoon, mid-monsoon, post-monsoon and ‘drying’ seasons (from April through November 1992). The experiment was designed to acquire remotely sensed data in the visible, near-infrared (NIR), thermal and microwave wavelengths from a variety of ground, aircraft and satellite platforms, with concurrent measurements of soil moisture, vegetation growth, and energy and water fluxes (summarized in Table 1).

Most ground- and aircraft-based measurements were limited to one site within WG, where a Metflux (MF) station was located with instrumentation for measuring both general meteorological conditions and estimating the surface energy fluxes. This site was in a hilly, grass-dominated subwatershed and was called the Kendall subwatershed.

The WG'92 experiment provided data at two scales for use in this analysis. First, the theory was tested at the local scale with ground-based radiometers acquired at the grass-dominated Kendall site. At this scale, it was possible to compare the results directly with conventional measurements of $E\Gamma$ rates on site. Then, the technique was
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>210</td>
<td>28 July</td>
<td>Cloudy</td>
<td>28 July</td>
<td>yes yes G and A</td>
<td></td>
<td></td>
<td></td>
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<td>11 August</td>
<td>Clear</td>
<td>11-12 August yes G</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>226</td>
<td>13 August</td>
<td>Marginal yes</td>
<td>13 August yes yes yes G</td>
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<td>27 August yes G and A</td>
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<tr>
<td>250</td>
<td>6 September</td>
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<td></td>
<td>yes G and A</td>
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<td></td>
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<tr>
<td>251</td>
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<td>Clear</td>
<td></td>
<td>yes G and A</td>
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<tr>
<td>258</td>
<td>14 September</td>
<td>Cloudy</td>
<td>15-16 September yes A</td>
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<td></td>
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</tr>
<tr>
<td>274</td>
<td>30 September</td>
<td>Clear yes</td>
<td>1 October yes yes yes G and A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>290</td>
<td>16 October</td>
<td>Clear</td>
<td>16 October yes yes yes G and A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>306</td>
<td>1 November</td>
<td>Clear</td>
<td>yes</td>
<td>yes yes yes G and A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>322</td>
<td>17 November</td>
<td>Clear</td>
<td>yes</td>
<td>18-20 November yes yes yes G and A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

DOY = day of year 1992, TM = Landsat Thematic Mapper, ERS-1 = ERS-1 Synthetic Aperture Radar, OD = atmospheric optical depth, RP = radiosonde atmospheric profile, VS = vegetation survey measurements at 2-6 sites, SM = gravimetric soil moisture at 4-5 sites, STR = ground- (G) and aircraft-based (A) measurements of surface temperature and reflectance.

demonstrated for all grasslands within the region using Landsat Thematic Mapper (TM) data, which covered the southeast corner of Arizona and included 10 distinct vegetation biomes (Fig. 2(a)). The next subsections address the instrumentation and data processing that were the basis for the subsequent analysis.

4.1. Biome designation

A land cover map for this region was extracted from the Prototype 1990 Conterminous US Land Cover Characteristics Data Set CD-ROM (Loveland et al., 1991). Thirty-six land cover classes were identified for south-east Arizona and these were merged to form ten associations that were characteristics of this area: agriculture, sage-oak, desert grassland, conifer forest, oak-grassland, sage-creosote, creosote-mesquite, sage-grassland, alpine forest and playa. The playa 'association' is actually a large, dry, barren lakebed located in the northern part of the TM scene.

4.2. Meteorological-energy flux (Metflux)

The Metflux station at Kendall provided local-scale measurements of net radiation, air temperature, surface temperature, wind speed and direction, relative humidity, solar radiation, photosynthetically active radiation (PAR), soil heat flux, soil moisture and soil temperature. The energy balance was determined by taking measurements of net radiation ($R_n$), soil heat flux density ($G$), and the temporal variance of air temperature.
Fig. 2. Images of the study region depicting (a) vegetation biomes [1: agriculture, 2: sage-oak, 3: grassland, 4: conifer, 5: oak-grass, 6: sage-creosote, 7: creosote-mesquite, 8: sage-grass, 9: alpine, and 10: Wilcox Playa] and (b) elevation [with symbols designating Ft. Huachuca (airstrip), Tombstone (box grid), Kendall (circle) and Lucky Hills (windmill)]. Images from DOY 162 depicting, (c) air temperature, (d) wind speed, (e) surface temperature and (f) SAVI.
which was used in computing sensible heat flux density ($H$) and solving for latent heat flux density ($LE$) as a residual, i.e., $LE = -(R_{n} - G - H)$. The instrumentation and theoretical foundation for these stations were described in detail by Kustas et al. (1994). They found that the $LE$ values obtained with this instrumentation were within 20% of...
those obtained with the more traditional eddy correlation technique under unstable conditions.

At each MF site and throughout the WG watershed, rainfall was monitored using automated weighing raingages. Weekly cumulative rainfall amounts for Kendall during the WG'92 experiment (Fig. 3(a)) are indicative of the seasonal rainfall pattern in this
Fig. 3. For the Kendall grassland site during 1992, (a) weekly cumulative rainfall amounts (mm), (b) vegetation biomass (gm $^{-2}$) and cover (%), and (c) volumetric soil moisture (%) to 5 cm depth.

region. That is, annual precipitation is about 300 mm total, with approximately two thirds falling during the 'monsoon' season (July—September). It should be noted, however, that the rainfall during Spring 1992 was greater than normal.

For the regional-scale analysis, maps of $T_a$ and $U$ were created from meteorological data obtained from 13 existing weather stations located throughout the TM scene (Rahman et al., 1994). Hourly air temperature data from the weather stations were interpolated to the satellite overpass time (10:15 am). These values were then normalized to sea surface level using a static lapse rate of temperature (obtained from radiosonde data) to obtain sea level air temperature over the region. A two-dimensional linear interpolation method was then used to grid the temperature over the whole region with a grid size of 120 by 120 m. This was then used to regenerate surface-averaged and topography-adjusted temperatures of the grids (Fig. 2(c)) with the help of digital elevation data (Fig. 2(b)) of the region and the static lapse rate of temperature. Similarly,
wind speed values from the thirteen weather stations were interpolated over the region using the above-mentioned two-dimensional interpolation method (Fig. 2(d)).

4.3. Vegetation and soils

At the Kendall site, monthly measurements of vegetation cover, height and volume by species, total leaf area index (LAI), plant biomass, litter, and plant water content were made throughout the experimental period in grazed and ungrazed sites with both southeast- and northwest-facing slopes. In response to the seasonal rainfall patterns in this region, the vegetation biomass and cover are generally highest during the monsoon season (e.g., Kendall grassland biomass measurements, Fig. 3(b)). Gravimetric soil moisture samples of the upper 5 cm (three replications) were collected at four or five sites within WG, including Kendall, during each Landsat overpass (Fig. 3(c)).

4.4. Atmospheric measurements

Measurements of incident solar illumination were made with a solar radiometer over the time period from sunrise to solar noon and total optical depth of the atmosphere was determined from the slopes of Langley plots (Slater et al., 1987). Total optical depth was partitioned into Rayleigh, aerosol, and ozone optical depths using the procedure described by Biggar et al. (1990). These values were used as input to the Herman—Browning radiative transfer code (RTC) to provide at-satellite radiance values for several assumed values of surface reflectance, ranging from 0.02 to 0.6 (Moran et al., 1992). Based on these RTC-derived values and the Landsat TM sensor calibration, TM digital data were converted to surface reflectance factors. Radiosonde profiles of atmospheric temperature, water content and pressure were also available during each Landsat overpasses at nearby Ft. Huachuca military base. These values were used as input to the Lowtran RTC to allow retrieval of surface temperatures from the Landsat thermal data (Washburne, 1994).

4.5. Remotely sensed spectral data

Ground-based observations of surface reflectance and temperature were made over designated areas at the Kendall site using Exotech 2-band radiometers, a Barnes Modular Multispectral Radiometer (MMR) and Everest infrared thermometers (IRT) during the Landsat overpasses. The ground target covered a large area (480 m by 120 m) over both north- and south-facing slopes representing multiple resolution cells (pixels) of the Landsat TM sensor. Radiometers were mounted in portable yokes at a height of 2 m (resulting in a spatial resolution of about 0.5 m) and deployed over a fine sampling grid resulting in nearly 400 samples over the Kendall target.

\[2\] The use of company names and brand names are necessary to report factually on available data; however, the authors' affiliations neither guarantee nor warrant the standard of the product, and the use of the name implies no approval of the product to the exclusion of others that may also be suitable.
For a number of overpass dates (Table 1), a Cessna aircraft was flown along two parallel transects intercepting the locations of 8 Metflux sites within WG, with instruments including a 4-band radiometer with Landsat Thematic Mapper (TM) filters (TM1–TM4), an IRT, color video camera and occasionally a thermal-IR scanner. The aircraft flew at a nominal altitude of 100 m above ground level (resulting in a spatial resolution (a pixel) of approximately 25 m diameter on the surface) and flights were scheduled to coincide with the Landsat overpass times (approximately 10:30h).

Eight Landsat TM scenes images were acquired to monitor the seasonal surface changes associated with the dry, monsoon and post-monsoon seasons (Table 1). The nadir-looking Landsat TM sensor has six reflective bands ranging from 0.45 to 2.35 μm with 30 m spatial resolution and one thermal band (10.42–11.66 μm) with a spatial resolution of 120 m. These images were registered and surface reflectance and temperature were retrieved from the digital numbers. We found that the atmospherically-corrected values of TM-derived surface reflectance compared well with ground- and aircraft-based measurements at the Kendall site (Root Mean Squared Error (RMSE) = 0.007). The atmospherically-corrected values of TM-derived surface temperature were close to values measured by ground- and aircraft-based instruments, but were consistently overestimated by 1.5 to 3°C (Washburne, 1994). This point is important because an error of 1°C in surface temperature could result in an error of 50 W m\(^{-2}\) in the estimation of \(LE\) (Moran et al., 1989). Examples of the \(T_s\) and SAVI images for one date in 1992 (Day Of Year (DOY) 162) are included in Fig. 2(e) and (f).

5. Results

The WDI theory was tested at the local scale using ground-based data at Kendall and at the regional scale using Landsat TM data covering the semiarid region located in the southeast corner of Arizona.

5.1. Local results with ground-based measurements at Kendall

As described in a previous section, yoke-based spectral data were acquired over a grid at the Kendall site, bracketing the time of the Landsat overpass. These data were combined with the Metflux measurements of \(R_n\), \(G\), \(T_s\), \(U\), and VPD to compute WDI for the site on each of 13 days. Unlike the agricultural site for which Moran et al. (1994a) demonstrated the WDI, the Kendall grassland site never reaches full-cover: at a maximum, the vegetation cover is only about 45%. Thus, it becomes difficult to compute the values for points 1 and 2 in Fig. 1. For the agricultural site, Moran et al. (1994a) computed \(r_s\) in Eqs. (5) and (6) based on an estimate of surface roughness (\(z_0\)) equal to 0.13\(h\), where \(h\) was maximum plant height. For the Kendall site, we computed \(r_s\) for points 1 and 2 based on estimates of \(z_0\) measured on site during the peak of vegetation biomass in 1990 (Stannard et al., 1994). Then, we computed the VIT trapezoid to extend from SAVI = 0.1 (minimum cover) to SAVI = 0.5 (maximum cover). We computed the VIT trapezoid for each date using this refinement and determined WDI based on an average of the yoke-based measurements of \(T_s\) and SAVI on each date.
Fig. 4. Comparison of instantaneous actual evapotranspiration (W m$^{-2}$) derived from the WDI model with measurements of evapotranspiration using the Metflux instrumentation. Numbers above symbols represent the day of year 1992.

With a computation of potential $E\Gamma_p$ for each date, we were able to retrieve instantaneous actual $E\Gamma$ (converted to energy units: Wm$^{-2}$) from the WDI and compare that with the values of LE measured with Metflux instrumentation (Fig. 4). The 'modeled' values based on the VIT trapezoid compared well with the Metflux values (RMSE = 29 W m$^{-2}$ over a range of LE values from 200–450 W m$^{-2}$), though there was a trend for the modeled LE to overestimate the measured values in most cases (Mean Absolute Difference (MAD) = 45 W m$^{-2}$). This uncertainty was comparable to the uncertainty of conventional ground-based instruments, such as the Bowen ratio and eddy correlation. Kanemasu et al. (1987) reported that LE values could vary by as much as 100% between measurements made with Bowen ratio instruments, and up to 15% with eddy correlation instruments. Kustas et al. (1994) reported that the Metflux measurements of LE were within 20% of those values measured using the eddy correlation technique.

5.2. Regional results with satellite-based measurements

Based on the good results obtained at the local scale, a similar analysis was conducted at the regional scale based on four of the eight Landsat TM scenes acquired during WG'92. The other four images were excluded from this analysis due to variable cloud cover within the scene that could influence the results. The chosen dates were DOYs 162, 178, 274 and 306. DOYs 162 and 178 were just prior to the monsoon season when the vegetation and soil were dry; DOY 274 was post-monsoon season, when the vegetation was more dense but soil conditions were again dry; and on DOY 306, vegetation was mostly senescent (Table 2 and Fig. 3).

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The terms $E\Gamma$ and $E\Gamma_p$ are used interchangeably with the terms LE and LE$_p$, where the former are in units of mm h$^{-1}$ or mm day$^{-1}$ and the latter are expressed in energy units (W m$^{-2}$ or MJ m$^{-2}$ day$^{-1}$).
Table 2
Meteorological and edaphic conditions at Kendall on the dates of the Landsat TM overpasses

<table>
<thead>
<tr>
<th>DOY 1992</th>
<th>Date</th>
<th>Last rain: date and amount</th>
<th>Amount of rain in last 30 days</th>
<th>Soil Moisture</th>
</tr>
</thead>
<tbody>
<tr>
<td>162</td>
<td>10 June</td>
<td>30 May, 0.5 mm</td>
<td>32 mm</td>
<td>2%</td>
</tr>
<tr>
<td>178</td>
<td>26 June</td>
<td>30 May, 0.5 mm</td>
<td>2 mm</td>
<td>2%</td>
</tr>
<tr>
<td>274</td>
<td>30 September</td>
<td>20 September, 0.7 mm</td>
<td>7 mm</td>
<td>3%</td>
</tr>
<tr>
<td>306</td>
<td>2 November</td>
<td>28 October, 11 mm</td>
<td>14 mm</td>
<td>NA</td>
</tr>
</tbody>
</table>

* Rain in August: 117 mm.

Information from the four TM scenes was combined with the interpolated map of \( T_s \) to create images of SAVI and \( T_s - T_a \). These data were stratified by vegetation biome and plots of SAVI by \( T_s - T_a \) were made for each biome. Examples of these are shown for the sage-creosote and alpine biomes and a bare dry playa. The characteristic trapezoidal shape is apparent for the sage-creosote biome (Fig. 5). This would suggest that the vegetation and soil conditions within this biome range from sparse to dense vegetation and from dry to wet soil conditions. However, there are a variety of other variables that could contribute to this scatter, including effects of topography on SAVI.

![Fig. 5. Scattergram of \((T_s - T_a)\) by SAVI from the four Landsat TM scenes for the sage/creosote biome.](image-url)
and $T_s - T_a$, inadvertent inclusion of vegetation other than that specified by the labeled biome, and the variability of atmospheric scattering and absorption at varying altitudes. The scatterplot for the alpine biome (Fig. 6) forms an oval shape rather than a trapezoid. This is due to the near-constant vegetation cover, resulting in consistently high values of SAVI. It is notable, however, that the shape and location of the alpine scatterplot relative to the $x$-axis ($T_s - T_a$) vary with date. This is due not only to changes in the evaporative cooling, but also to differences in such meteorological conditions as incoming solar radiation, wind speed and vapor pressure.

The scattergram associated with the barren playa (Fig. 7) could be used as a baseline from which to understand the scattergrams of the other biomes. First, comparison of the SAVI value for each date provides a check on the overall data quality. Since the playa supports only minimal vegetation growth, the SAVI should be very consistent with time. If the SAVI were to vary, it would indicate either a problem with the atmospheric correction of the reflective data or a misregistration of the image. Second, the magnitude and range of the $T_s - T_a$ data provide an indication of the surface water status and variability, respectively. For example, the hottest temperatures were associated with DOY 178 (the day of driest conditions, Table 2) and the greatest range of temperatures was associated with DOY 162 (the day associated with more recent rainfall, and possibly, variable soil moisture). Spatial variability in rainfall is high in this area.

![Diagrams of scattergrams for different dates](image-url)
Thus, the shape of the data scatter from the barren playa should corroborate the basic knowledge of the vegetation cover, soil moisture status, and meteorological conditions at the site on that day.

Since general information about the grassland biome was known from our local-scale analysis at Kendall, it was possible to compute a trapezoid for this biome for each overpass date. The trapezoid computation was based on the average $T_a$ and $U$ values for the grassland biome derived from the interpolated $T_a$ and $U$ maps. We used values of VPD, $R_n$, and $G$ measured at the Metflux station on each date at Kendall, assuming that these values would be similar for other grasslands in the region at the same general elevation. As with the local-scale analysis, values of surface roughness for points 1 and 2 were based on prior analysis of the grassland biome in 1990 (Stannard et al., 1994) at SAVI = 0.5 (50% vegetation cover). The VIT trapezoids presented in Fig. 8 encompass the data from 0% to 50% vegetation cover and, assuming that the 'warm' and 'cool' edges are linear, can be extended to SAVI = 0.70 (100% vegetation cover).

The VIT trapezoids for the grassland biome (extended to 100% vegetation cover) encompassed the majority of the data on each date (Fig. 8). It is notable that data scatter on DOY 178 (the driest date) did not approach the theoretical 'cool' edge of the trapezoid. On the other three dates, the scatter touched and sometimes exceeded the cool edge. On DOY 162 (the wettest date), the highest density of points was located in the middle of the trapezoid, unlike the other days where the highest density of points was located close to the 'warm edge'.
Based on Eq. (13), a computation of potential instantaneous evaporation ($LE_p$), and the VIT trapezoids from Fig. 8, we were able to compute the actual instantaneous evaporation rate associated with each pixel within the grassland biome in the Landsat TM image. These estimates are presented in the form of a histogram bounded by values of $LE = 0$ and $LE = LE_p$, in Fig. 9 (see also Table 3). For each day, the majority of the $LE$ values were between $LE = 0$ and $LE = LE_p$, though there was a tendency for some estimates of $LE$ to be erroneously less than zero (e.g., DOYs 178, 274, and 306). It appeared that either the VIT trapezoid method tended to underestimate the temperature of the warm edge or the surface temperature data from the Landsat TM images were overestimated. Based on the right-hand side of Eq. (8), it is possible that errors in the computation of the warm edge could be due to errors in the calculation of $R_a$, $G$ or $r_a$. However, since the method worked well at the local scale (Fig. 4), it appears that these inputs were reasonable. Another source of error could be the calibration and atmospheric correction of the remotely-sensed data, causing an overestimation of the surface.
temperature. In fact, Washburne (1994) found that the satellite temperatures computed from these 1992 images were consistently warmer (by up to $3^\circ$C) than aircraft and ground-based measurements. For the conditions at WG, an error of $1^\circ$C in surface temperature could result in an error of $50 \text{ W m}^{-2}$ in the estimation of $LE$. Thus, this $3^\circ$C overestimation of surface temperature would account for the majority of the pixels for which $LE$ was underestimated.

Table 3

<table>
<thead>
<tr>
<th>DOY 1992</th>
<th>$T_s$</th>
<th>$U$</th>
<th>$R_n$</th>
<th>$G$</th>
<th>VPD</th>
<th>$T_s$</th>
<th>SAVI</th>
<th>WDI</th>
</tr>
</thead>
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<tr>
<td>162</td>
<td>25.6</td>
<td>2.0</td>
<td>670</td>
<td>308</td>
<td>3.99</td>
<td>31.3</td>
<td>0.20</td>
<td>0.40</td>
</tr>
<tr>
<td>178</td>
<td>23.8</td>
<td>2.8</td>
<td>660</td>
<td>313</td>
<td>4.84</td>
<td>35.0</td>
<td>0.18</td>
<td>0.60</td>
</tr>
<tr>
<td>274</td>
<td>23.8</td>
<td>5.3</td>
<td>562</td>
<td>250</td>
<td>3.43</td>
<td>28.8</td>
<td>0.20</td>
<td>0.62</td>
</tr>
<tr>
<td>306</td>
<td>16.2</td>
<td>5.0</td>
<td>471</td>
<td>228</td>
<td>1.28</td>
<td>19.6</td>
<td>0.16</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Fig. 9. A frequency histogram of the evaporation rates ($\text{W m}^{-2}$) computed using the VIT trapezoid for all pixels within the grassland biome (from Fig. 8). The vertical dashed lines represent the points where $LE$ equals zero and $LE$ equals the potential ($LE_p$). The Water Deficit Index (WDI) was computed from the average of all these data and used to indicate the water status of that biome on each date (Table 3).
6. Concluding remarks

Based on analysis at the local and regional scale, it appears that this approach is reasonable and has some potential for mapping evaporation rates of heterogeneous landscapes. Assuming that the vegetation type is known (using a biome map or other information), the inputs required were

1. spatially-distributed meteorological measurements of $T_a$, $U$, $R_n$, $G$, and VPD.
2. remotely sensed measurements of $T_s$ and SAVI, and
3. estimates of $z_o$, and $d_o$.

In this analysis, we used measurements of $R_n$ and $G$ at a local grassland site. The approach would be more regionally applicable if the techniques described by Jackson et al. (1985) and Clothier et al. (1986) were used to map $R_n$ and $G$ over heterogeneous areas. Our values of $z_o$ and $d_o$ were taken from measurements at Kendall in 1990. For regional applications, it would be preferable to use reasonable estimates of $z_o$ for general biome types, such as those suggested by Reiners et al. (1994). Future work with the data set presented here will be focused on these two refinements.

The sources of error for application of this approach at the regional scale are numerous and need to be analyzed for impact on the results. A sensitivity analysis will be performed to investigate the effects of topography on surface reflectance and temperature measurements, the error associated with applying an atmospheric correction computed at one altitude to an image composed of multiple altitudes, and the sensitivity of the procedure to differences in surface emissivity. The error associated with variations in emissivity could be reduced by estimating the surface emissivity from measurements of surface reflectance, as suggested by Van de Griend and Owe (1993).

One idea that was mentioned briefly here and deserves further consideration is the use data from a large bare soil site within the image as a baseline from which to understand the scattergrams of the other biomes. This approach would only be applicable to certain scenes but may hold some promise to minimize the meteorological measurements required by the technique.

Acknowledgements

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References


Appendix D:

An operational approach for vegetation water deficit estimation in a heterogeneous region

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Concept of ‘Vegetation Index/Temperature’ (VIT) trapezoid has been previously used to estimate the Water Deficit Index (WDI) of agricultural crops and rangeland. In this study we applied the same procedure at a regional scale with other biomes in the heterogeneous semiarid lands of southeast Arizona. This procedure was used as an operational tool for the management of these lands. Wind speed, maximum vegetation height, Leaf Area Index (LAI) and Vapor Pressure Deficit (VPD) were the only ground data used with the remotely sensed spectral data of the region for this purpose. Results showed that this procedure could be used for different semiarid biomes, even though some problems arose in the calculation of the trapezoid. Sensitivity analysis showed that the VIT trapezoid, and hence the WDI estimation, is mostly sensitive to wind speed. An error of 1 m/sec in the wind speed measurement could induce an error of 6° C in the estimated temperature. Erroneous leaf area index and vapor pressure deficit can also induce error in trapezoid calculation and ultimately in WDI estimation. Also, it was seen that the use of a single trapezoid for calculation of WDI of all biomes would cause a 10% to 35% error.
INTRODUCTION

Arid and semi-arid lands cover almost 40% of the earth's land surface and play a very important role in the global water and energy balance. Hence it is necessary to develop an operational technique for monitoring and predicting surface conditions of these lands. These lands are characterized by a variety vegetation types (biomes) due to varying topography and related drainage patterns. The water deficit of the different biomes is one of the important factors that needs to be monitored and predicted for the proper management of the arid and semiarid lands.

Generally water deficit is monitored by estimating actual evapotranspiration (ET) rate and comparing that to potential ET computed from meteorological measurements. Techniques for estimating actual ET with conventional methods, such as Bowen ratio (Bowen, 1926) or eddy correlation (Wesely et. al, 1970) are not suitable for these lands due to lack of easy accessibility and also due to the varied topography, vegetation cover and soil conditions (Blyth and Dolman, 1993). In recent years, there has been an increased effort to estimate evapotranspiration rates of large areas using remotely sensed data combined with meteorological data and physical energy balance models. One approach that has been found to be particularly useful is the incorporation of remotely-sensed spectral data with the ground-based meteorological data in some form of the Penman-Monteith (P-M) equation (Monteith, 1973). Moran et al. (1996) adapted this approach to estimate the water deficit and ET of a grassland with considerable accuracy.
They termed this adapted approach the ‘vegetation index/temperature (VIT) trapezoid approach’. This ‘VIT trapezoid’ approach is based on the hypothesis that a trapezoidal shape would result from a plot of measured surface minus air temperature ($T_s - T_a$) versus a soil adjusted spectral vegetation index SAVI (Figure 1). The edge of the trapezoid connecting points 1 and 3 has an ET rate equal to potential ET (PET). The edge of the trapezoid connecting points 2 and 4 has an ET rate of zero. Assuming a linear relation between ET and surface temperature, the VIT trapezoid can be used to estimate the water deficit of any biome. An index of the water deficit, termed as water deficit index (WDI, which is equal to $[1 - ET/PET]$ ) could be derived from the location of the measurements of $T_s - T_a$ and SAVI within the VIT trapezoid. A detailed discussion of the trapezoid approach and the assumptions behind WDI is given by Moran et al (1994).

Since the arid and semiarid lands of the world support multiple biomes in addition to grassland, it is necessary to estimate WDI of all the arid/semiarid biomes in order to be able to monitor and manage these lands. Using the theoretical justification of WDI concept and remotely sensed and meteorological data from southeast Arizona, an effort was made to produce maps of WDI for that area. The overall goal was to apply the VIT trapezoid approach in an operational manner that would allow monitoring and assessment of the heterogeneous semi-arid lands. As such, best estimates of model inputs (e.g., leaf area index (LAI), plant height) were made for each biome based on published studies (BATS, Dickinson et. al, 1986). Meteorological parameters (wind speed, vapor pressure deficit (VPD) and air temperature) were obtained from weather stations located within
and near the borders of the LANDSAT thematic mapper (TM) images of the study area. TM images were acquired on four dates and registered to the site.

It was found in previous studies that the shape and size of the VIT trapezoid for each biome on each day varied depending on the values of meteorological and vegetation parameters used in the trapezoid model. Since the shape and size of the trapezoids are used to estimate the WDI of a biome, it was necessary to find out the sensitivity of the trapezoid to changes in the values of meteorological and vegetation parameters. This would enable us to estimate the error associated in the estimation of WDI of heterogeneous lands using the trapezoid procedure as an operational system.

The next section presents a brief outline of the VIT trapezoid procedure in short.

Objectives of the present study were as follows:

1) To test the application of VIT trapezoid and WDI theory for all the dominant biomes of southeast Arizona for four days in 1992.

2) To produce WDI maps of the study area for those four days.

3) To test the sensitivity of the VIT trapezoid to the values of meteorological and vegetation parameters used in model parameterization.

**VIT TRAPEZOID THEORY**

Previous studies have shown that a negative correlation exists between surface temperature \((T_s)\) and spectral vegetation indices (such as normalized difference VI (NDVI) and soil adjusted VI (SAVI)). Nemani and Running (1989) found that for dense
vegetation, the slope of the $T_s$/NDVI relation was related to canopy resistance. Nemani et al. (1993) found that the $T_s$/NDVI slope was negatively correlated to surface moisture in case of sparse vegetation. Friedel and Davis (1994) reported that the observed negative correlation between $T_s$ and NDVI was dependent on fractional vegetation cover and also on the difference of land cover classes. Moran et al. (1994) found that by using surface minus air temperature ($T_s - T_a$) instead of surface temperature ($T_s$) alone, it was possible to utilize the Penman-Monteith (P-M) equation of ET estimation (Monteith, 1973) to define the theoretical boundaries of ($T_s - T_a$)/SAVI relation for a biome for the whole range of fractional cover, from bare soil to full cover, and over the whole range of surface moisture conditions, from dry to well-watered situation. A trapezoidal shape (VIT trapezoid) would result from a plot of measured $T_s - T_a$ and SAVI (Figure 1). The vertices of the trapezoid would correspond to 1) well-watered full-cover vegetation, 2) water-stressed full-cover vegetation, 3) saturated bare soil, and 4) dry bare soil.

Jackson et al. (1981) combined the P-M equation with a one-dimensional energy balance equation to derive a computation for canopy minus air temperature,

$$(T_c - T_a) = \frac{[r_o (R_n - G)/C_v]}{\gamma (1 + r_c/r_a)} \frac{[\Delta + \gamma (1 + r_c/r_a)]}{[VPD/[\Delta + \gamma (1 + r_c/r_a)]]}$$

where, $T_c$ is the canopy temperature ($^\circ$C), $T_a$ is the air temperature ($^\circ$C), $r_a$ is the stability-corrected aerodynamic resistance (s m$^{-1}$), $R_n$ is the net radiant flux density (W m$^{-2}$), $G$ is the soil heat flux density (W m$^{-2}$), $C_v$ is the volumetric heat capacity of air (J $^\circ$C$^{-1}$ m$^{-3}$), $r_c$ is the canopy resistance (s m$^{-1}$) to vapor transport, $\gamma$ is the psychrometric constant (kPa $^\circ$C$^{-1}$), $\Delta$ is the slope of the saturated vapor pressure-temperature relation (kPa $^\circ$C$^{-1}$), and
VPD is the vapor pressure deficit of the air (kPa). The stability-corrected aerodynamic resistance \( r_a \) was expressed by Mahrt and Ek (1984) and adapted for this application by Jackson et al (1981).

Moran et al (1994) used Eq. (1) to define the four vertices of the trapezoidal shape in a plot of \( T_s - T_a \) versus SAVI that encompassed all possible combinations of SAVI and \( T_s - T_a \) for one vegetation type on one day. That is, for full-cover, well-watered vegetation,

\[
(T_s - T_a)_n = [r_{ea}(R_n - G)/C_v][\gamma(1 + r_{cp}/r_{a})]/\{\Delta + \gamma(1 + r_{cp}/r_{a})\}] - [VPD/\{\Delta + \gamma(1 + r_{cp}/r_{a})\}]
\]

where \( r_{cp} \) is the canopy resistance at potential evapotranspiration and the subscript \( n \) of \( (T_s - T_a)_n \) refers to vertex \( n \) in Figure 1. For full cover vegetation with no available water,

\[
(T_s - T_a)_2 = [r_{a}(R_n - G)/C_v][\gamma(1 + r_{ex}/r_{a})]/\{\Delta + \gamma(1 + r_{ex}/r_{a})\}] - [VPD/\{\Delta + \gamma(1 + r_{ex}/r_{a})\}]
\]

where \( r_{ex} \) is the canopy resistance associated with nearly complete stomatal closure. For saturated bare soil, where \( r_c = 0 \) (the case of a free water surface),

\[
(T_s - T_a)_3 = [r_{e}(R_n - G)/C_v][\gamma/(\Delta + \gamma)] - [VPD/(\Delta + \gamma)]
\]

and for dry bare soil, where \( r_c = \infty \) (analogous to complete stomatal closure),

\[
(T_s - T_a)_4 = [r_{e}(R_n - G)/C_v]
\]

Values of \( r_{cp} \) and \( r_{ex} \) were obtained from measurements of stomatal resistance \( r_s \) and LAI:

\[
r_{cp} = r_s/LAI \text{ and } r_{ex} = r_s/LAI
\]
where LAI > 0 (Monteith, 1973). Values of minimum and maximum stomatal resistance ($r_{sp}$ and $r_{sx}$ respectively) were obtained from published values for many plant types under a variety of atmospheric conditions or when published values were not available, values of $r_{sp} = 25$-100 s m$^{-1}$ and $r_{sx} = 1000$-1500 s m$^{-1}$ were found to be reasonable. The calculation of $r_a$ requires some estimate of surface roughness. For points 1 and 2 of the trapezoid, maximum plant height of each biome were used to estimate the surface roughness. For points 3 and 4, a minimum plant height common to all biome (0.1 m) was used.

Moran et al (1994) showed that using the above mentioned Eqs. 2-5 and the well-known Crop Water Stress Index (CWSI) concept of Jackson et al. (1981), the WDI of a biome could be formulated as,

$$WDI = \frac{[(T_s - T_a) - (T_s - T_a)_r]}{[(T_s - T_a)_m - (T_s - T_a)_x]}$$  \hspace{1cm} (7)

where $m$, $r$ and $x$ subscripts refer to the theoretical minimum, measured and theoretical maximum values of $(T_s - T_a)$ respectively for any point inside the trapezoid (Fig. 1). Graphically WDI is equal to the ratio of distances AC/AB in Figure 1. Thus WDI = 0.0 for well-watered conditions and WDI = 1.0 for maximum stress conditions.

For any given value of SAVI, the minimum and maximum values of $(T_s - T_a)$ was computed by,

$$(T_s - T_a)_m = c_o + (SAVI)/c_i$$  \hspace{1cm} (8)

and

$$(T_s - T_a)_x = d_o + (SAVI)/d_i$$  \hspace{1cm} (9)
where $c_0$ and $c_1$ are the offset ($^\circ$C) and slope ($^\circ$C) respectively of the line connecting points 1 and 3 in Figure 1, and $d_0$ and $d_1$ are the offset ($^\circ$C) and slope ($^\circ$C) respectively of the line connecting points 2 and 4 in Figure 1. For subsequent analyses, the line connecting points 1 and 3 of the VIT trapezoid will be termed the “cool” edge and the line connecting points 2 and 4 will be termed the “warm” edge.

**DATA**

The WDI theory was tested for regional application using data from an experiment, referred to as WG’92. WG’92 was conducted during the dry, early-monsoon, mid-monsoon, post-monsoon and drying seasons (from April through November, 1992) in the southeast corner of Arizona. This experiment was designed to acquire remotely sensed data in the visible, near infra-red (NIR), thermal and microwave wavelengths from a variety of ground, aircraft and satellite platforms. Concurrent measurements of soil moisture, vegetation growth and energy and water fluxes were also measured in some of the experimental sites inside the study area. Moran et al (1996) and Rahman et al (in press) have given a full description of this study area. A full description of the WG’92 experiment is given by Washburne (1994). Landsat TM data were used in the present study to demonstrate the WDI approach on the seven dominant biomes of the area. A short description of the biome data, TM data, meteorological data and model parameterization are given in the next sections.

**Biome description:**
Biome data for southeast Arizona was retrieved from the GAP data set (ART Program, Univ. of AZ). The original GAP data set of 30m spatial resolution was resampled to 120 m resolution to match the TM thermal band resolution. Seven biome associations were identified that were the characteristics of this area: grass, brush, agriculture, mixed-oak, paloverde, pine and a playa (Figure 2). The “playa” is actually a large dry, almost barren lakebed located in the upper middle part of the area. Maximum vegetation height and maximum LAI of each biome were derived from the GAP source data. It is relevant here to mention that this biome designation is different than the one used by Moran et al. (1996).

**TM images:**

TM images of the area were registered using the ground control points as described by Washburne (1994). Images from four days in 1992 were relatively cloud free. Those were DOYs (day of year) 162, 178, 274 and 306. DOYs 162, 178 and 274 had some cloud cover scattered on the images. For the purpose of the present study, the cloud-laden pixels were discarded from the images. Also, due to the high solar zenith angle (48°- 53.2°) during the TM image acquisition time (10:15 LST) and the hilly topography of the region, many pixels on the images were shaded. Those shaded pixels were also discarded for this analysis. In Moran et al. (1996), clouded and shaded pixels were not discarded. Discarding these cloudy and shaded pixels was necessary due to the fact that $R_n$ for the whole area was calculated based on the assumption that the surface is exposed to direct sunlight.
From these cloud- and shade-free TM images, surface temperature ($T_e$) maps of the region were derived using the band-6 digital numbers (DN) and radiosonde data in a radiative transfer code (RTC). SAVI maps for the four DOYs were created using the reflectance from TM bands 3 and 4, as described in Equation 4 of Moran et al (1996).

As mentioned above, TM data from four DOYs in 1992 were useful for the present analysis. DOYs 162 and 178 (June 10th and 26th respectively) were just prior to the monsoon season when vegetation and soil were dry and air temperature was high due to summer. DOY 274 (September 30th) was in post-monsoon season, when vegetation was dense but soil was again dry, and air temperature was lower due to the advent of winter. DOY 306 (November 2nd) was in the drying season when vegetation was senescent and air temperature was cool due to winter.

**Meteorological data:**

Maps of $T_a$, $U$ and VPD were created from meteorological data obtained from 13 weather stations located throughout the TM scene (Rahman et al, 1994). The procedure of extrapolating point based meteorological data to spatially continuous maps are briefly described here.

Hourly air temperature ($T_a$) data from the weather stations were interpolated to the satellite overpass time (10:15 AM). Elevation of these weather stations were known. Using these elevations and the pseudo lapse rate of air temperature from radiosonde data acquired from nearby fort Huachuka Army Base, these point temperatures were
normalized to sea level. Then these point data were extrapolated to make a spatially continuous map of \( T_s \) at sea level at a grid scale of 120 m by 120 m. Using the digital elevation model (DEM) of the region and the lapse rate, spatially continuous \( T_s \) of the region was regenerated from the sea level gridded \( T_s \). This way, a surface-averaged and topography-adjusted \( T_s \) map of the region was generated for four dates.

Hourly wind speed data were collected from the weather stations and interpolated at the satellite overpass time. Due to the lack of any known method of spatially extrapolating wind speed over a large terrain of heterogeneous surface cover and varied topography, point values of wind speed were extrapolated over the region at a grid scale of 120 m by 120 m. Also the VPD values at the weather stations were extrapolated over the region similarly. A description of the procedure of creating \( T_a \) and \( U \) map and the resulting maps are also given by Moran et al. (1996). Values of \( R_n \) and \( G \) were estimated for the whole area using the method described by Rahman (1993).

**RESULTS AND DISCUSSION**

**VIT trapezoids:**

Scatterplots of SAVI by \((T_s - T_a)\) were made for each of the seven biomes for four DOYs (Figure 3[A-G]). Also the VIT trapezoids for each biome on each DOY were overlaid on the relevant scatterplots. The trapezoids in Figure 4 were made to encompass a range of SAVI from 0.0 to 0.8, based on the prior knowledge of the vegetation of the area.
It can be seen from figure 3[A-G] that for grassland, the majority of the data points were inside the VIT trapezoids. For DOY 162, data scatter started from near the cool edge of the trapezoid and did not reach the warm edge. This indicates that on DOY 162 the surface had enough moisture in the grassland and water deficit was not too high. DOYs 178, 274 and 306 had some data that exceeded the warm edge of the trapezoid. Also DOY 306 had some data outside the cool edge, even after screening the images for shaded pixels.

Overall, the scatterplots and the trapezoids had shown some common trends. In all the biomes except for a few data points in agriculture, DOY 162 had data scatter inside the trapezoid, implying that the VIT trapezoid concept was working for that DOY. DOYs 178 and 274 had data points exceeding the warm edge in all biomes except playa. It should be recalled here that playa was almost barren. This trend of DOYs 178 and 274 give rise to a possibility that the calculation of warm edge of VIT trapezoids involved some errors for these two DOYs. Data scatter for all biomes crossed the cool edge of trapezoids for DOY 306. There might be some error associated in the calculation of the cool edge of trapezoid for DOY 306. It is also noticeable that for DOY 306 (a cold day), the data scatter had a tendency of staying away from the warm edge for all the biomes except grass and brush. Errors associated with the calculation of the warm and cool edges of the VIT trapezoid is reported in the ‘sensitivity analysis’ section.

**WDI maps:**
Using Equation 11, the WDI maps of the biomes for the four DOYs in the year 1992 were produced (Figure 4[A-D]). Pixels that were shaded or cloudy and also those whose \((T_s - T_a)\) values fell outside the trapezoids in figure 3[A-G] were discarded from WDI calculation. These discarded pixels are colored red in figure 4[A-D]. The range of WDI were scaled from 0.0 to 1.0 for all DOYS. The urban area was not under any biome classification. So the urban area was discarded from the WDI calculation. Due to the lack of any distinct riparian vegetation class along the river (San Pedro), the pixel values in the riparian area fell outside the trapezoids and they were also discarded.

Spatial variation of WDI values all over the maps in four DOYs are clearly visible. The valley in between the mountains (in the right hand side of the map) had high WDI values. But it can be seen that this valley was also spotted with low WDI areas. Those were irrigated agricultural areas. The areas with higher WDI values had more water stress in those DOYs and these maps could be used as operational tools for managing these water stressed areas better.

**SENSITIVITY ANALYSIS**

**Errors in input variables:**

From Equations 2-7 above, it was found that there were two main vegetation parameters, i.e., maximum and minimum plant height \((h_x \text{ and } h_m)\), and maximum and minimum leaf area index \((\text{LAI}_x \text{ and } \text{LAI}_m)\), and two main meteorological parameters i.e., wind speed \((U)\) and VPD, which were used in the calculation of the four points of
trapezoid. Plant height for calculating points 3 and 4 of trapezoid were fixed at a minimum plant height (0.1 m) for all biomes. Maximum plant height (hₐ) for each biome were used for calculation of points 1 and 2 and that varied biome to biome (taken from GAP data and shown in Table 1). Hence in this sensitivity analysis, these four input variables (hₓ, LAIₓ, U and VPD) were varied over a range of ±0.1 m, ±1, ±1 m/sec and ±0.1 kPa respectively using a Monte Carlo simulation with 10000 iterations. These variations were within the range of errors in field estimations of these variables.

Model inputs for a grassland on DOY 162 was used as standard and the simulations were run varying these four input variables. The resulting sensitivity in the warm and cool edges of the trapezoid are shown in Figure 5. Only the non-parallel arms of the trapezoid (i.e., warm and cool edges) are shown in the figure. Solid lines are the original trapezoid lines and the dotted lines are the range of maximum movement of the lines in response to the changes of the relevant input variables. It can be seen that none of the cool and warm edges of the trapezoid are very sensitive to hₓ. For LAIₓ variation, point 2 is sensitive, but point 1 is only slightly sensitive. All four points of the trapezoid were found to be sensitive to U. Points 1 and 3 were sensitive to the changes in VPD.

It is clear from the Figure 5 that even though errors in LAI and VPD would cause errors in the trapezoid calculation, the most sensitive input variable in the calculation of trapezoid for any biome is wind speed U. For an error of 1 m/sec in U, the error in trapezoid Tₛ - Tₐ was as large as 6°C. In this study, emphasis was given to operational methods for obtaining model inputs. Hence the wind speed was obtained by a simple
interpolation of wind speed measurements at 13 weather stations in the study site. Since wind speed was found to be the most sensitive input, it was of interest to determine what would be the error induced by this simple interpolation method. A second, more computation-oriented and time consuming method was used to estimate the surface wind fields of the area. Large-scale meteorological data were assimilated into a model simulation using the Regional Atmospheric Modeling System (RAMS, Pielke et al., 1992). The vegetation coverage used in the RAMS model was determined from the LANDSAT NDVI, as described by Toth (1996).

Wind speed map for DOY 274 at a grid of 3840 m by 3840 m square was produced using the RAMS model. DOY 274 was used for this test since that was the most windy day among all four DOYs of this study. Wind speed map originally produced by simple interpolation (at a grid size of 120 m by 120 m) was resampled to fit the grid size of the RAMS model wind speed map. A difference map of these two maps was also produced. These maps are shown in figure 6. RAMS model wind speed map is more sensitive to topographic features than the simple interpolation map. In the RAMS map, winds were relatively strong in the gaps between the mountain ranges and relatively light in the lee of the ranges. The mean difference between the wind images by these two procedures was 7.6° C with a standard deviation of 3.4° C.

**Single trapezoid for multiple biomes:**

A test was also done to asse the error if a single trapezoid were used for all the biomes in one DOY rather than using biome-specific trapezoids. Again, DOY 162 was
selected because trapezoids for all biomes showed better result for that DOY for all biomes (refer to Figure 3). The trapezoid for the grass biome was selected to be used because it was the largest and it seemed to cover the data scatter for all other biomes. This trapezoid was overlain on the data scatter from DOY 162 for all seven biomes (Figure 7). It can be seen that data scatter of all the biomes perfectly fits inside the grass trapezoid. To find out what error would be associated with using a single trapezoid for all biomes, WDI values of the data scatter were calculated using the biome-specific trapezoids (WDI\textsubscript{real}) and also using the grass trapezoid (WDI\textsubscript{grass}) for all biomes. Mean, standard deviation (std) and coefficient of variation (cv) of the absolute values of differences of these two WDI values (i.e., |WDI\textsubscript{real} - WDI\textsubscript{grass}|) were calculated and are shown in Table 2. Since the grass trapezoid was used, WDI for grass were excluded from this analysis. It can be seen from the cv values in Table 2 that the pine biome would have the biggest error (≈35%) in WDI calculation if grass trapezoid was used instead of pine trapezoid. The second biggest error (≈28%) would occur with playa. The rest of the biomes would have an error of approximately 10% to 14% in WDI estimation if the biome-specific trapezoids were not used.

CONCLUSION

The WDI map showed the spatial distribution of water stress over the study area. It was interesting to see that water stress of the area varied on different DOYs. Since the production of WDI maps require only a small number of vegetation and meteorological
input parameters and satellite images, these maps can conveniently be used as an operational tool to identify the mostly water stressed areas at a given time period. This water stress information can then be used to predict fire potential for forest areas or animal grazing limitation for rangelands. Also, for large-scale agricultural areas this information can be used for irrigation scheduling. For riparian areas this information can be used to predict the health of the riparian ecosystems. This study showed that the WDI procedure has a potential of being used as an operational tool for arid/semiarid land monitoring and management.

The VIT trapezoid concept for the seven biomes worked well for DOY 162. For DOYs 178 and 274, most of the data scatter were inside the trapezoid, but some exceeded the warm edge. Data scatter exceeded the cool edge in DOY 306. Sensitivity analyses showed that error in wind speed could lead to large errors in the trapezoids. Also erroneous LAI and VPD measurements could cause substantial errors. The tendency of data to exceed the warm edge on DOYs 178 and 274 and to exceed the cool edge on DOY 306 suggest that there were some error in the trapezoid calculation. Since wind speed and VPD were simply extrapolated from point measurements to spatially continuous maps without taking into account the topography, there always remained a possibility of error in the extrapolated values. Wind speed image derived by RAMS model showed that there was most probably errors in wind speed estimation by the simple interpolation procedure. Also the LAI values obtained from GAP data were not a fixed
value, they had a range of values. Taking the largest values of LAI (from GAP data) for LAI, of each biome in the present study could have added some error.

It was also found that using a single trapezoid for all biomes would introduce error in WDI estimation. Since this study showed that even when biome-specific trapezoids were used, there remained some chances of error from the vegetation and meteorological input variable estimation, it would not be advisable to use a single trapezoid for all biomes.
Table 1: Maximum plant height and maximum LAI of the biomes used in the present study. The values were taken from the source documents of GAP data set.

<table>
<thead>
<tr>
<th>Biome name</th>
<th>Maximum plant height (m)</th>
<th>Maximum LAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pine</td>
<td>55</td>
<td>16</td>
</tr>
<tr>
<td>Mixed Oak</td>
<td>16</td>
<td>10</td>
</tr>
<tr>
<td>Grass</td>
<td>0.5</td>
<td>3</td>
</tr>
<tr>
<td>Brush</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Paloverde</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>Agriculture</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Playa</td>
<td>0.1</td>
<td>0.3</td>
</tr>
</tbody>
</table>
Table 2: Mean, standard deviation (S.D.) and coefficient of variation (CV) of the differences of WDI values using biome specific trapezoids and grass trapezoids for six biomes on DOY 162.

<table>
<thead>
<tr>
<th></th>
<th>agri</th>
<th>brsh</th>
<th>moak</th>
<th>pine</th>
<th>plvd</th>
<th>plya</th>
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<tbody>
<tr>
<td>Mean</td>
<td>0.19</td>
<td>0.09</td>
<td>0.13</td>
<td>0.13</td>
<td>0.24</td>
<td>0.06</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.02</td>
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<tr>
<td>CV</td>
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<td>0.13</td>
<td>0.14</td>
<td>0.35</td>
<td>0.09</td>
<td>0.27</td>
</tr>
</tbody>
</table>
Advanced Resource technology (ART) Program, 1996, School of Renewable natural resources, University of Arizona, Bioscience East, room 325, Tucson, AZ 85721


Figure captions:

Figure 1: The hypothetical trapezoidal shape that would result from the relation between 
$(T_s - T_a)$ and the SAVI (ranging from 0.1 for bare soil to 0.8 for full cover vegetation). For any point at C, the WDI can me measured as AC/AB. 
(Taken from Moran et. al, 1996).

Figure 2: Biome map of the study area. Urban area, San Pedro river, valley and the mountain are also shown in the map.

Figure 3: Scatterplots of $T_s - T_a$ vs. SAVI for seven biomes for four DOYs in 1992. Trapezoids for each biomes are overlaid on the scatterplots.

Figure 4: WDI maps for four DOYs. ‘A’ is DOY 162, ‘B’ DOY 178, ‘C’ DOY 274 and ‘D’ DOY 306.

Figure 5: Sensitivity of the trapezoid due to the four input variables, $h_x$, LAI, U and VPD. Trapezoid was found to be highly sensitive to the variation of U.

Figure 6: Resampled wind image, RAMS model wind image and the difference wind image for DOY 274. Grid size of these images was 3840 m square.
Figure 7: Grass trapezoid for DOY 162 used with scatterplots of all seven biomes. Since grass trapezoid was the biggest one it was used so that the data scatter stays inside the trapezoid.
Figure 1: Soil-Adjusted Veg. Index (SAVI) vs. Ts-Ta (C) for different vegetation conditions:

1. Well-watered Vegetation
2. Water-Stressed Vegetation
3. Saturated Bare Soil
4. Dry Bare Soil
Figure 2
Figure 3
Figure 3
Figure 3
Figure 3
Figure 3
Figure 3
Figure 5
A) Resampled wind image

B) RAMS model wind image

C) Difference wind image (A - B)

Figure 6
Figure 7
Figure 7