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Use of Remote Sensing for Monitoring Evaporation over Managed Watersheds

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Abstract

The USDA ARS Walnut Gulch Experimental Watershed (WGEW) has been the site for numerous interdisciplinary experiments focused on the use of remote sensing for estimating distributed evaporation (*E*). This report documents a selection of the remote sensing techniques that have been applied at WGEW and reports the resulting accuracies of estimates of *E*, along with the advantages and disadvantages of each technique. This selected techniques were contrasted with an operational remote sensing approach for monitoring *E* implemented by the Bureau of Reclamation for the Lower Colorado River Basin.

Introduction

Monitoring evaporation (*E*) at watershed scales is important for assessing the effect of climate and management on natural ecosystems. This report describes techniques used to evaluate *E* with remote sensing, which is the only technology that can efficiently and economically provide distributed estimates of *E* on a regional scale. These techniques are presented in three classes, termed here empirical approaches, physically-based analytical approaches, and numerical models (similar to classes first defined by Kustas and Norman, 1996). Empirical techniques are of two types. One uses the spatially-distributed multi-spectral image data to extrapolate a single (or multiple) *in situ* measurement(s) of *E* to a larger, heterogenous surrounding region. Another uses an empirical relation between a time series of *in situ E* measurements and multi-spectral measurements, and then applies that relation to multi-spectral images to produce maps of *E*. For such empirical techniques, it is necessary to have *in situ* conventional instrumentation for measuring *E* using such techniques as eddy correlation or Bowen ratio. Physically-based, analytical techniques are based on a direct evaluation of energy balance (and thus *E*) through a combination of remotely sensed measurements of surface reflectance and temperature with *in situ* meteorological measurements. Such analytical techniques generally provide a single hourly or daily estimate of *E* associated with the time and date of the remotely sensed data acquisition. Numerical models have been used to overcome this temporal limitation by using remotely sensed measurements as a source of intermittent grid-based information for soil-vegetation-atmosphere (SVAT) models to evaluate regional *E* continuously on an hourly or daily basis. Both analytical and numerical techniques are preferable when *in situ* measurements of *E* are not available, but they require a high degree of accuracy in the remotely sensed measurements of surface conditions and many input parameters related to soil and vegetation properties which are not readily available at regional scales.

This report offers examples of empirical, analytical and numerical techniques applied to the Walnut Gulch Experimental Watershed (WGEW) southeast of Tucson Arizona (Figure 1) and documents the resulting accuracies of estimates of *E*. To put this work into perspective, a description is also given of the technique implemented by a consortium of government agencies to determine *E* for the Lower Colorado River basin. This report should provide a framework for assessing the opportunities and limitations of remote sensing for evaluating watershed-scale *E*, and should encourage technology transfer efforts and interdisciplinary field experiments to investigate applications of this unique technology.

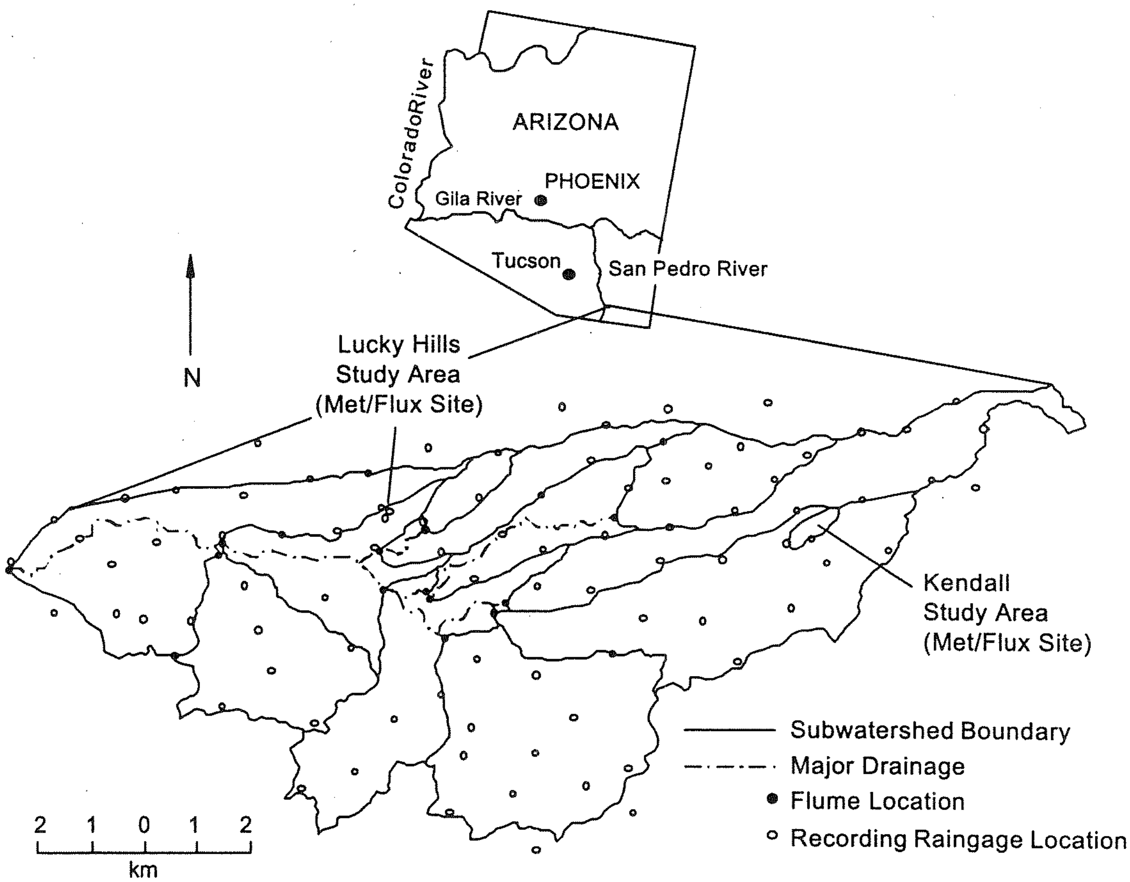

Figure1. Schematic illustrating the location and boundaries of the USDA ARS Walnut Gulch Experimental Watershed (WGEW) in Arizona. Illustration of the rain gage network, flume locations for measuring streamflow, subwatershed boundaries, and main drainage pattern (see Renard et al. (1993) for more information about WGEW).

Background Theory

Most procedures for estimating energy balance components from remote sensors and ground-based meteorological instruments are based on the one-dimensional form of the energy balance equation (Jackson, 1985), i.e.,

$$\lambda E = R_n - G - H, \tag{1}$$

where λE[1] is the latent heat flux density, R_n is the net radiant flux density, G is soil heat flux density, and

[1] Evaporation (E) is often represented in units of mm h^{-1}, but can also be expressed in energy units, where λE is the latent heat flux density (W m^{-2}). Though expressed in different units, the terms E and λE are interchangeable. To avoid confusion herein, the term E will represent evaporation rate in units of depth (mm h^{-1} or mm d^{-1}), and λE will represent latent heat flux density (in units of W m^{-2} or MJ d^{-1}). For further clarification on evaluation of Eqs. 1-5, readers are encouraged to consult the treatise by Monteith (1981) and the books by Brutsaert (1982) and Jensen et al. (1989).

values of λE, G and H are positive when directed away from the surface.

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

$$R_n = R_{S\downarrow} - R_{S\uparrow} + R_{L\downarrow} - R_{L\uparrow} = (1-\alpha)R_{S\downarrow} + (1-\varepsilon_s)R_{L\downarrow} - R_{L\uparrow} \tag{2}$$

where the subscripts S and L signify solar (shortwave) radiation (0.15 to 4 μm) and longwave radiation (> 4 μm) respectively, and the arrows indicate the flux direction (↓=incoming, ↑=outgoing). The parameter α is the surface shortwave albedo and ε_s is the surface emissivity. The variables $R_{S\downarrow}$, α and ε_s have been estimated with remotely sensed spectral data using empirical approaches and physically-based models (Jackson et al., 1985; Pinker et al., 1995; Van de Griend and Owe, 1993). Incoming longwave radiant flux density $R_{L\downarrow}$ has been estimated from ground-based measurements of air temperature and vapor pressure using the relation

$$R_{L\downarrow} = \varepsilon_a \sigma T_a^4, \tag{3}$$

where $\varepsilon_a = 1.24(e_o/T_a)^{1/7}$ (Brutsaert, 1975), σ = the Stefan-Boltzmann constant (W m^{-2} K^{-4}), T_a = air temperature (K), and e_o = vapor pressure (mb) at T_a (Jackson et al., 1985). The outgoing longwave radiation ($R_{L\uparrow}$) can be obtained from the surface radiative temperature,

$$R_{L\uparrow} = \varepsilon_s \sigma T_{rad}^4, \tag{4}$$

where ε_s = surface emissivity and T_{rad} = surface temperature (K) measured by a thermal radiometer.

The G term, though traditionally measured with temperature and heat flow sensors buried just beneath the soil surface, can be determined by a relation between G/R_n and spectral reflectance factors in the red and near-infrared (NIR) spectral bands (Clothier et al., 1986; Kustas et al., 1993).

With R_n and G estimated by remote sensing methods, sensible heat flux density is normally expressed as

$$H = \rho c_p(T_{aero} - T_a)/r_{ah}, \tag{5}$$

where ρc_p is the volumetric heat capacity (≈ 1150 J m^{-3} C^{-1}), T_{aero} is the surface aerodynamic temperature (Norman and Becker, 1995) and r_{ah} is a resistance to heat transfer (s m^{-1}). The resistance to heat transfer can be computed as a function of windspeed, atmospheric stability and surface roughness (Brutsaert, 1982). In practice, T_{aero} is usually replaced by T_{rad}. To account for differences in T_{aero} and T_{rad} which can be as large as 10°C for sparsely vegetated targets (Kustas, 1990; Choudhury et al., 1986), empirical and numerical methods have been developed to adjust either T_{rad} or r_{ah} (see review by Zhan et al.,1996).

Conventional Approaches for Measuring Evaporation

Theoretical developments such as those described in the previous section are generally dependent upon experimental data for verification. There are a variety of conventional approaches for measuring evaporation, ranging from simple to complex and having a range of accuracies and spatial scales.

At the watershed scale, E is generally determined using an energy balance approach (Bowen ratio) or a mass transfer method (eddy correlation) with commercial instrumentation. The Bowen ratio method allows values of hourly λE to be obtained from temperature and humidity measurements,

$$\beta = \gamma\, (K_h/K_v)\, (\Delta T_a/\Delta eo), \tag{6}$$

where β is the Bowen ratio ($H/\lambda E$), γ is the referred to as the psychrometric constant (2.453 MJ kg^{-1} at 20 C), K_h and K_v are the eddy transfer coefficients for sensible and latent heat, respectively, and ΔT_a and Δe_o are the differences in air temperature in C and vapor pressure in kPa over the same elevation difference, Δz. The accuracy of the method decreases with decreasing flux of water vapor, or when there is low evaporative demand (e.g., at night). A description of the Bowen ratio equipment was provided by Spittlehouse and Black (1980).

The eddy correlation method was proposed by Swinback (1951) based on the theoretical description of the mean vertical flux of water vapor

$$E = (0.622/P)\,\rho\,\overline{w'e'}, \tag{7}$$

where P is atmospheric pressure (kPa), w' is the instantaneous deviation of vertical wind speed from the mean vertical wind (w) at height z, and e' is the instantaneous deviation of the partial water vapor pressure from the mean at height z. Evaluation of Eq. (7) is accomplished using vertical anemometers and vapor pressure sensors with short sampling intervals (hundredths of seconds) to determine w' and e' in short, successive periods of time (tenths of seconds). This method is amenable to field use in routine measurements for extended periods, e.g. months or years (Kanemasu et al., 1979).

Other approaches that have been used to measure evaporation rates include the inflow-outflow method for monitoring evaporation from catchments (Holmes, 1984) and portable gas assimilation chambers (Reicosky, 1981). A limitation of all the techniques described in this section is that they yield essentially point values of evaporation, and therefore, are applicable only to a homogeneous area surrounding the equipment that is exposed to the same environmental factors. An evaluation of the spatial distribution of evaporation over large heterogeneous areas would be prohibitive using these conventional point measurement techniques.

Empirical and Semi-Empirical Methods

When *in-situ* measurements of E are available using instrumentation to evaluate the Bowen ratio or eddy correlation, it is possible to use one station as a reference site, and compute energy balance components for other locations within the watershed based on remotely sensed data (surface temperature and reflectance). Humes et al. (1994) present a good example of this basic concept for the WGEW semiarid rangeland watershed. Based on a framework developed by Gash (1987), Humes et al. used ground-based data from one meteorological/flux station in WGEW together with aircraft-based remotely sensed data to compute instantaneous values of spatially distributed surface energy fluxes at seven other locations within the watershed. Two cases were evaluated: (1) the case in which the reference site was treated as a flux station; that is measurements of the components of the surface energy balance (Rn, G, H and λE) were used directly as estimates of fluxes at the reference site, and (2) the case in which the reference site is treated as a station providing only meteorological variables; that is the reference fluxes were estimated from meteorological data and remotely sensed measurements. Humes et al. (1994) reported that the availability of surface flux measurements at the ground-based stations improved the estimation of various components of Eq. (1) by approximately 5-10 Wm^{-2}. They found that R_n could be estimated very well across the watershed, and that the root mean squared error (RMSE) of λE was approximately 50 Wm^{-2} for a range of values from 100-400 Wm^{-2}.

When a time series of *in situ* measurements of E and remote sensing data are available, it is possible to correlate E measurements with coincident spectral measurements to develop an empirical relation that can be applied to other locations. One of the most widely applied approaches is based on a simplification of Eqs. (1) and (5), where daily E (E_d) is a presented as a function of daily R_n ($R_{n,d}$) and instantaneous measurements of T_{rad} and T_a ($T_{rad,i}$ and $T_{a,i}$),

$$E_d = R_{n,d} - B(T_{rad,i} - T_{a,i}). \tag{8}$$

or with further simplification, $E_d = A' - B'(T_{rad,i}-T_{a,i})$, where B, A' and B' are empirical coefficients (Jackson et al., 1977). Eq. (8) was modified by Seguin and Itier (1983) to include an exponent where $E_d = R_{n,d} - B''(T_{rad,i}-T_{a,i})^n$, where n was equal to 1.0 for stable conditions (where $T_{rad,i}>T_{a,i}$) and 1.5 for unstable conditions (where $T_{rad,i}<T_{a,i}$).

Moran et al. (1994b) evaluated Eq. (8) based on flux measurements during the dry and wet seasons at WGEW and found a good correlation (r^2=0.87) between ($T_{rad,i}-T_{a,i}$) and ($E_d - R_{n,d}$), where the mean absolute difference (MAD) between modeled and measured values of E_d was 0.1 mm/day. They also found that empirical coefficient B was similar for WGEW grassland, irrigated pasture and dryland shortgrass in France, and grass and shrublands in Owens Valley. This should encourage further research with such approaches.

Physically-based Analytic Methods

The majority of physically-based, analytical techniques are based on direct evaluation of energy balance (Eqs. 1-5) through a combination of remotely sensed measurements of surface reflectance and temperature with *in situ* meteorological measurements. Such analytical techniques generally provide a single hourly or daily estimate of E associated with the time and date of the remotely sensed data acquisition. In the past decade, a multitude of studies have been conducted to develop sound methods for accounting for differences between T_{aero} and T_{rad} in evaluation of Eq. (5). As a result, single-source (Troufleau et al., 1994) and dual-source models (Norman et al., 1995; Lhomme et al., 1994) have been developed to offer a physically-based correction and avoid the need for empirical adjustments to r_{ah}. Reported estimates of H with such physical models are within 20-30% of measured H fluxes (Zhan et al., 1996), which is close to the level of uncertainty in eddy correlation and Bowen ratio techniques for determining the surface fluxes in heterogeneous terrain (Nie et al., 1992).

An example of a single-source model with an empirical adjustment to r_{ah} was reported for WGEW (Moran et al., 1994c). Moran et al. estimated R_n based on Eq. (2) where $R_{S\downarrow}$ was measured with a calibrated pyranometer, $R_{L\downarrow}$ was estimated from ground-based measurements of air temperature and vapor pressure using Eq. (3), $R_{S\uparrow}$ was obtained from data collected with down-looking multispectral sensors (according to Jackson, 1985), and $R_{L\uparrow}$ was obtained from the remotely measured surface temperature using Eq. (4). The soil heat flux, G, was estimated based on an exponential relation suggested by Jackson et al. (1987), where $G/R_n = 0.583e^{-2.13NDVI}$, and where $NDVI$ is the normalized difference vegetation index derived from reflectance in the NIR and red spectrum [$NDVI=(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})$] and related to the amount of green vegetation present. H was evaluated using Eq. (5), where two methods were tested to account for the additional heat transfer resistance associated with sparse vegetation.. The first method associated the additional resistance with the differences in transfer processes of heat and momentum by as a function of T_{rad}. The other attempted to divide the total resistance into it's component parts: one related to plant height, one to canopy structure, and an additional resistance to account for the effect of partial-canopy surface temperature. Moran et al. (1994c) reported that the mean absolute differences (MAD) between measured and modeled values were 50 Wm^{-2} for R_n (range of values 100-700 Wm^{-2}), 20 Wm^{-2} for G (range of values -15-215 Wm^{-2}), 33 Wm^{-2} for H (range of values 15-310 Wm^{-2}), and 40 Wm^{-2} for λE (range of values 0-340 Wm^{-2}). They pointed out that because λE was solved as a residual, there was a cumulative effect of errors associated with remotely sensed estimates of R_n, G and H.

In later work, Moran et al. (1996) circumvented the need for an empirical correction for the T_{aero} - T_{rad} difference by using another analytical approach. Moran et al. (1994a) proposed that the negative relation between $NDVI$ and (T_{rad} - T_a) was related to λE, which was driven by variations in evaporative cooling. They defined theoretical boundaries in the $NDVI/(T_{rad} - T_a)$ two-dimensional space using the Penman-Monteith equation (Allen, 1986). The boundaries define a trapezoid, which represented stressed and unstressed 100% vegetation cover at the upper two corners and represented wet and dry bare soil conditions at the lower two corners (Figure 2). In order to calculate the vertices of the trapezoid, measurements of R_n, e_o, T_a, and U were required, as well as vegetation specific parameters such as maximum leaf area index and maximum and minimum stomatal resistance. When applied to grasslands in WGEW, Moran et al. (1996) reported that the modeled values of λE based on the $NDVI/(T_{rad} - T_a)$ trapezoid compared well with *in situ* measurements of λE (RMSE = 29 Wm^{-2} over a range of λE values from 200-450 Wm^{-2}), though there was a trend from the modeled λE to overestimate the measured values in most cases.

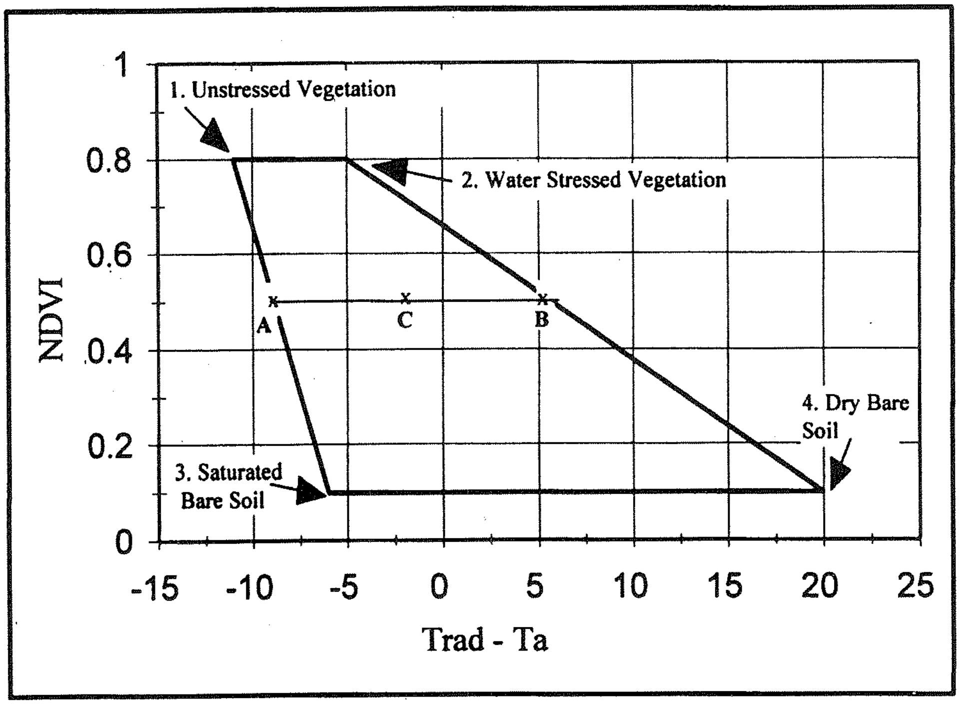

Figure 2. The trapezoidal shape that results from the theoretical relation between radiative temperature minus air temperature ($T_{rad} - T_a$) and the normalized difference vegetation index (NDVI). With a measurement of ($T_{rad} - T_a$) at point C, it would be possible to equate the ratio of actual to potential E with the ratio of distances CB and AB.

Numerical Models

Assimilating remotely sensed data in numerical soil-vegetation-atmosphere (SVAT) models combines the spatial coverage of the imagery with the temporal frequency of the model to provide accurate, distributed information describing plant and soil conditions on a daily or hourly basis. Assimilation is generally achieved by an iterative model "calibration" procedure using intermittent spectral information to estimate several model parameters and/or initial conditions, thus increasing the model accuracy (e.g., Moran et al., 1995). The advantages of numerical models over empirical and analytical approaches are 1) they generally are based on the physics of energy transport in the SVAT system; and 2) they can simulate energy fluxes continuously and predict fluxes based on simulated meteorological conditions. One of the greatest difficulties in using such models for a spatially-distributed application is determining spatially-distributed meteorological information such as air temperature (T_a) and wind speed (U). The two studies described next in this section are examples of a combined remote sensing/modeling approach implemented at WGEW and a numeric approach with a mesoscale atmospheric model to produce large area meteorological fields of such model input parameters as T_a and U.

Nouvellon et al. (2000) demonstrated a combined remote sensing/modeling approach for a ten year period from 1990 to 1999 for the grassland region in WGEW (142 km^2) based on meteorological data from a station located in a sub-watershed (~1 km^2) , a map of soil types, and surface reflectance measurements from 25 Landsat Thematic Mapper (TM) images. The SVAT model, consisting of two submodels designed to simulate plant growth and water budget, was linked with a canopy radiative transfer model (RTM) through the simulated green leaf area index (GLAI). An iterative procedure was used to minimize the difference between simulated and measured *NDVI* by changing values of selected model initial conditions or input parameters. Parameters and initial conditions chosen to be re-parameterized/re-initialized were initial living root biomass (BR_{ini}) and maximum light use efficiency (ε_{qmax}) of absorbed photosynthetically active radiation (*APAR*). The difference between modeled and measured plant biomass for years 1990-1992 resulted in a RSME of only 11.7 g/m^2. In contrast, when the model was run with BR_{ini} and ε_{qmax} values based on published literature, the RMSE was nearly double at 19.3 g/m^2. Nouvellon et al. (2000) validated this remote sensing/modeling approach with *in situ* measurements of plant biomass and soil moisture; validation of modeled surface energy flux is in progress. The results presented in Figure 3 show the potential for using this approach to produce maps of *E* and root-zone soil moisture for WGEW grasslands for any day during the 10-year period.

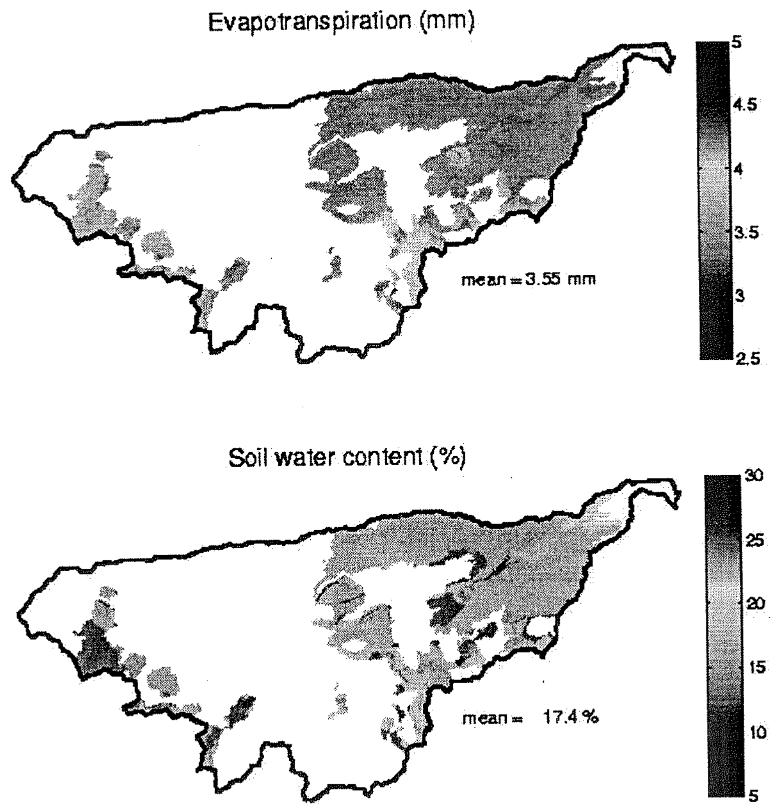

Figure 3. Images of evaporation (upper) and root-zone soil moisture (lower) for the grassland areas within WGEW derived from a numerical model calibrated with remotely sensed measurements (from Nouvellon et al., 2000) for 7 Sept. 1992. With this approach, it is possible to produce images of biomass, soil moisture, evaporation and other vegetation and soil information for any date in the 10-year period of the model run.

To address the issue of determining spatially-distributed meteorological information for a heterogeneous landscape, Toth (1997) tested an approach to retrieve spatially-distributed meteorological data at a fine 4-km resolution from a mesoscale meteorological model. The Regional Atmospheric Modeling System (RAMS) is a mesoscale meteorological model designed to predict the variability in surface atmospheric forcing arising from heterogenous land cover and complex topography (Pielke et al., 1992). The RAMS model was run in near real-time with basic boundary conditions estimated by approximately 30-km mesoscale "Eta" data produced by the National Weather Service's National Center for Environmental Prediction (NCEP). Local-scale information about surface characteristics was incorporated into the model using a two-way coupling of Landsat Thematic Mapper (TM) data with RAMS. The result was the generation of images of local-scale forcing variables at 4-km resolution over an area 230 by 230 km encompassing most of the semi-arid San Pedro River Basin (USPB: 7,600 km^2) in southeast Arizona at 6-hour intervals. Examples of the RAMS fields of air temperature, wind speed, water vapor mixing ratio, and precipitable water are included in Figure 4 for 9 June 1997. These fields have not yet been fully validated.

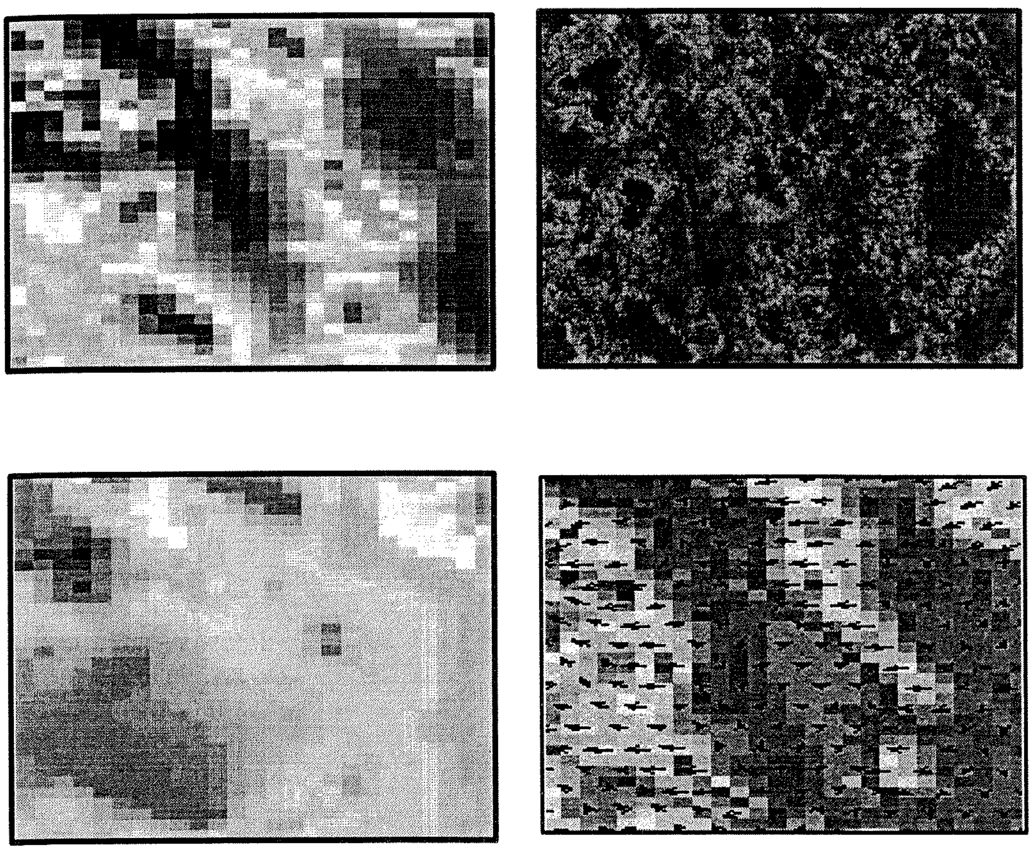

Figure 4. Fields of air temperature (upper left), wind speed (upper right) and water vapor mixing ratio (lower left) at 4-km resolution over a region of 100 by 100 km, derived from the Regional Atmospheric Modeling System (RAMS) for the Upper San Pedro Basin on 9 June 1997. North is at the top and WGEW is located in the lower right quadrant. A Landsat TM color composite image covering the same area at 100-m resolution (lower right) was included to illustrate the diverse topography and vegetation cover that influenced the large area variability in T_a and U.

Perspective

Several approaches utilizing remotely sensed data to estimate distributed E at the watershed scale have been described in the previous sections. Kustas and Norman (1996) summarized the state-of-the-art by listing the "issues" that are important for remote sensing of E from measurement and modeling studies and theoretical considerations. A revised list of these issues is included here:

1) T_{rad} is not equal to T_{aero}.
2) Most models are sensitive to errors in T_{aero} - T_a and U, yet the measurement of T_a and U at the time and location of the T_{rad} observation is not typically available.
3) Thermal emissivity is only known approximately on the pixel scale.
4) Atmospheric corrections and satellite calibrations contribute significant errors in the measurements of ρ and T_{rad} that are not always adequately known.
5) Remote observations are instantaneous, while integrated fluxes are desired on hourly, daily or longer time scales.
6) Continuous (hourly or daily) surface flux estimates are most useful and clouds cause remote observations to be intermittent.

Kustas and Norman (1996) reported that none of the 28 approaches they reviewed addressed all these issues. Considering that, it is understandable that very few remote sensing approaches have been implemented operationally at watershed or basin scales.

To understand the level of complexity that is suitable for operational estimates of E at the watershed scale, it is instructive to look at a system currently in practice for the Lower Colorado River Basin (study area ~20,000 km^2). Due to a U.S. Supreme Court decree, the Bureau of Reclamation (BR) was asked to provide an accounting for the use and distribution of water from the Lower Colorado River. BR joined with U.S. Geological Survey (USGS), Lower Basin States, and Bureau of Indian Affairs (BIA) to develop a method for estimating and distributing agricultural consumptive use to agricultural water diverters between Hoover Dam and Mexico. This system is known as the Lower Colorado River Accounting System (LCRAS) and is described in detail by the U.S.D.I. Bureau of Reclamation (1997). As part of LCRAS, a methodology was developed for estimating percentages of E for each diverter from an analysis of satellite images and estimated water-use rates of vegetation types within the boundaries of each diverter. E for each vegetation class was computed using 1) the reference values for short grass (E_o) provided local meteorological network stations and 2) vegetation-class-specific E coefficients. In this case, the remotely sensed images were used simply to identify the type and aerial extent of vegetation classes along the Lower Colorado River. In mathematical terms, the general equation for E by one vegetation class is

$$E_v = [\textstyle\sum_n (E_o K_c)] AC_c , \tag{9}$$

where E_v is the total monthly or annual E by one vegetation class for one diverter, $\sum_n$ is the summation over an amount of time, typically one month or year, E_o is the daily reference E values calculated with data from the meteorological station, K_c is the daily vegetation coefficient (Jensen, 1996) and AC_c is the acreage of one vegetation class for the diverter in question.

In contrast to the approaches applied at WGEW and presented in previous sections, the LCRAS did not attempt to relate the remote sensing data directly to E but only to vegetation class. Thus, LCRAS was able to circumvent (or minimize) the effects of the eight issues listed above. Furthermore, no attempt was made to evaluate E at a time scale finer than one month, thus reducing the potential measurement variability. The BR plans to improve LCRAS by estimating E using a surrogate vegetation coefficient derived from NDVI, but there are no plans to use remote sensing data to determine actual E from T_{rad} as described in most approaches herein.

Summary

There are a wide variety of techniques available to monitor *E* using remote sensing at watershed scales, as illustrated with examples at WGEW. The techniques ranged from simple, empirical approaches that could estimate the spatial distribution of *E* on the date of the image acquisition to more complex, numerical techniques that could estimate both the spatial and temporal distribution of *E*. The simplest, empirical approaches generally required instrumentation *in situ* to measure *E* at one location. Following development and testing, analytical and numerical approaches did not require *in situ* instrumentation, but often required distributed meteorological information and other ancillary vegetation and soil data. In any case, the examples here showed that remote sensing techniques can be implemented to monitor *E* at the watershed scale with reasonable accuracy.

The examples of state-of-the-art research at WGEW were contrasted with the operational approach implemented by BR for the Lower Colorado River Basin. It is apparent that there is a gap between the approaches under development at research institutions and the needs of agencies responsible for monitoring large area *E*. Future work should be conducted with input from the potential clients to ensure that the application of this technology suits the accuracy requirements and technological capabilities of the end users.

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