Evaporation from Nonvegetated Surfaces: Surface Aridity Methods and Passive Microwave Remote Sensing

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(Manuscript received 16 June 1998, in final form 29 October 1998)

ABSTRACT

The use of remotely sensed near-surface soil moisture for the estimation of evaporation is investigated. Two widely used parameterizations of evaporation, the so-called α and β methods, which use near-surface soil moisture to reduce some measure of potential evaporation, are studied. The near-surface soil moisture is provided by a set of L- and S-band microwave radiometers, which were mounted 13 m above the surface. It is shown that soil moisture measured with a passive microwave sensor in combination with the β method yields reliable estimates of evaporation, whereas the α method is not as robust.

1. Introduction

The estimation of surface aridity at the land surface with remote sensing is an area of growing importance for the estimation of evaporation (Kustas et al. 1998). In particular, passive microwave remote sensing is being increasingly tested in the field to measure near-surface soil moisture (Schmugge et al. 1998). The flux–gradient transfer relationships for latent heat flux that make use of near-surface soil moisture measurements are the ''alpha'' or ''beta'' formulations, which can be written, respectively, as

$$\alpha q_s^* - q_a = \frac{E}{r_a} \tag{1}$$

and

$$\beta(q_s^* - q_a) = \frac{E}{r_a}, \tag{2}$$

where q_s^* is the saturated water vapor density at the soil surface, q_a is the water vapor density at some measurement height, E is the mass rate of evaporation, and r_a is resistance of the atmosphere to water vapor transport. The α and β parameters are generally taken to be functions of the surface soil moisture content θ, and they range from a value of 1 when the soil surface is saturated to a value of 0 when there is absolutely no water present in the soil. The α function takes the place of the relative humidity at the soil surface, which would scale q_s^* in a normal flux–gradient relationship (the ''true'' relative humidity at the soil surface is very difficult to measure, hence the attractiveness of an α func-

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tion). The problem of determining α is akin to the problem of determining ''skin temperature'' for the estimation of sensible heat flux (Cahill et al. 1997; Verhoef et al. 1997), and a bulk formulation is taken in both cases to deal with measurement difficulty. The β function, on the other hand, scales the gradient that would exist if the soil surface were saturated to the actual value of the water vapor density gradient.

Typically (1) and (2) are written using Monin–Obukhov similarity theory as

$$\alpha q_s^* - q_a = \frac{E}{ku_*\rho}\left[\ln\left(\frac{z}{z_{0v}}\right) - \Psi_v\left(\frac{z}{L}\right)\right] \tag{3}$$

and

$$\beta(q_s^* - q_a) = \frac{E}{ku_*\rho}\left[\ln\left(\frac{z}{z_{0v}}\right) - \Psi_v\left(\frac{z}{L}\right)\right], \tag{4}$$

respectively, where z is the measurement height of q_a, k (=0.4) is the von Kármán constant, u_* is the friction velocity, z_{0v} is the scalar roughness length for water vapor, Ψ_v is the stability correction function for water vapor, and L is the Obukhov length.

A number of different relationships for $\alpha(\theta)$ and $\beta(\theta)$ have been proposed; a list appears in Ye and Pielke (1993). The first model for α used came from the thermodynamic relationship for specific humidity in a porous medium derived by Edlefsen and Andersen (1943),

$$\alpha = \exp\left(\frac{\psi g}{RT_s}\right), \tag{5}$$

where ψ is the matric potential, g is the gravitational acceleration, R is the gas constant, and T_s is the soil surface temperature (in absolute units in this equation). The α method is attractive because it is rooted in soil physics. However, this model has been found to be unsatisfactory in practice (Kondo et al. 1990; Mahfouf and Noilhan 1991). As a result, empirical models for α have been developed (e.g., Noilhan and Planton 1989). Since β does not mimic a physical variable such as relative humidity, models for this parameter are empirically based. Only a few of the proposed relationships seem to have been based on actual measurements (i.e., E, u, RH, T_a, and T_s), which were then used with the flux–gradient equations to solve for α and β (e.g., Barton 1979; Avissar and Mahrer 1986; Kondo et al. 1990). Development of models to estimate α and β as a function of soil surface moisture content and total soil porosity has been explored by Ye and Pielke (1993). Mihailovic and coworkers (Mihailovic et al. 1995a, 1995b) investigated a number of proposed α and β parameterizations by implementing them in numerical land–atmosphere interaction models and comparing the model-predicted latent and sensible heat fluxes to Bowen ratio–measured heat fluxes. Essentially in practice, all these surface resistance schemes are site dependent and ultimately must be calibrated for a particular region for application. It is also desirable to relate α and β to measurable quantities, which for remotely sensed data are surface soil moisture and skin temperature.

In this paper we study the different roles that α and β play in scaling the specific humidity terms in the flux–gradient equation. There should be different amounts of experimental uncertainty associated with each parameter, and this leads to different degrees of accuracy in the resulting latent heat (LE) estimates. Furthermore, the assumption that α or β can be described as a function of θ alone may be true to a greater degree for one parameter than the other. In this study, we examine the question of which method of surface moisture parameterization is more suitable based on careful field measurements using passive microwave remote sensing. In doing so, we will present formulations for $\alpha(\theta)$ and $\beta(\theta)$ for a given soil, but the specific functions derived are not the primary goal of the paper. Rather, the robustness of each method to estimate evaporation will be investigated, and specific features of the two methods will be examined.

2. Experiment and analysis methods

The data used in the analysis presented herein were collected during the summer of 1995 at Davis, California, at the University of California's Campbell experimental tract. A comprehensive set of micrometeorological and surface soil moisture measurements were taken to solve for α and β from (3) and (4), respectively. All instruments recorded measurements every 20 min and were available for yeardays (DOY) 164–177, except for days 165, 170, and 171, when the failure of one or more instruments meant that application of (3) or (4) to solve for α and β was not possible. Details on the measurements and calculations follow.

The Campbell field was kept unvegetated for the course of the measurements used here since the α and β methods refer to bare soil evaporation conditions. The field was planed smooth before the commencement of the experiment to minimize surface roughness effects on the radiometer measurements. The evaporation and sensible heat flux were measured using an eddy correlation system consisting of a three-dimensional sonic anemometer and a krypton hygrometer mounted at a height of 1.17 m. There was an uninterrupted fetch of more than 200 m upwind from the eddy correlation system. The use of the three-dimensional sonic anemometer allowed measurement of the friction velocity u_* also. Only daytime periods with positive latent heat flux are used here. Air temperature and humidity were measured at 1.17 m, and the soil surface temperature was measured with two separate infrared thermometers (IRTs), which were placed approximately 100 m apart from one another. One of the thermometers (located at the flux station) was mounted at 0.94 m with a viewing angle of 45°, while the other (at the radiometer) was mounted at 13 m with a viewing angle of 10°. The two

IRTs gave essentially the same values for surface temperature, so that only the measurements from the lower IRT are used in the analysis. Both q_s^* and the saturated specific humidity for the air q_a^* were calculated using the surface and air temperature measurements. The actual specific humidity for the air q_a is then obtained from q_a^* and the measured relative humidity. The Obukhov length L is defined as

$$L = \frac{-u_*^3 \rho}{kg\left[\left(\frac{H}{T_a c_p}\right) + 0.61E\right]}, \tag{6}$$

where H is the sensible heat and c_p is the heat capacity of the air. The Businger–Dyer formulation (Brutsaert 1982) for the stability-correction function Ψ_v was used. The scalar roughness length was calculated using the formula derived by Brutsaert (1975),

$$z_{0v} = z_{0m} \exp[-k(7.3 z_{0+}^{1/4} \mathrm{Sc}^{1/2} - C_{d0}^{-1/2})], \tag{7}$$

where z_{0+} is the roughness Reynolds number defined as $u_* z_0/\nu$, where ν is the viscosity of the air, and Sc is the Schmidt number for air (=0.595). Following Cahill et al. (1997) a value of 9.5 was used for $C_{d0}^{-1/2}$, instead of the value of 5 originally suggested by Brutsaert (1975).

Surface soil moisture was measured during the experiment by a pair of experimental passive microwave radiometers developed by the Hydrology Laboratory of USDA–ARS in Beltsville, Maryland, and NASA Goddard Space Flight Center. The radiometers operated in the S-band (2.65 GHz) and the L-band (1.4 GHz) ranges of the spectrum, and their field of view was approximately 16 m^2. Since the correlation length of the Campbell tract soil (Yolo silt loam) has been found to be 1 m (Parlange et al. 1992), the footprint contained several independent soil moisture ''point'' samples. The emission data taken by the radiometers were converted into volumetric moisture content using the algorithm developed in Jackson et al. (1997). Algorithm parameters were calibrated on site.

The measurement depth of passive microwave radiometers is a question of current research interest; however, an in-depth treatment is beyond the scope of this paper. In addition, the radiometer does not measure a simple depth average of the soil moisture. Moisture closer to the surface is weighted more than that at deeper depths, and the weighting function changes as the distribution of soil moisture changes. For the purposes of our analysis, we will use the results of Jackson et al. (1997), which found that the S-band radiometer measured soil moisture to 2 cm, while the L-band radiometer measured soil moisture to 5 cm.

The local environmental temperatures at the Davis site sometimes exceeded the design range for the microwave radiometers during the middle of some days. This resulted in some erratic behavior that was easily identified. Data from these time periods were not used.

TABLE 1. Regression statistics for the best-fit exponential functions for α and β as a function of $1/T_{s,\mathrm{abs}}$ in Figs. 1 and 2. The statistics are for the log-transformed linear regression of $\ln\alpha$ or $\ln\beta = \alpha + \beta/T_{s,\mathrm{abs}}$. Here r^2 is the variance (correlation coefficient squared).

	$\ln\alpha$ vs $1/T_{s,\mathrm{abs}}$
Intercept	−20.35
Std error of intercept	0.48
Slope	5912
Std error of slope	146
r^2	0.88

3. Results and discussion

The goal of this paper is to explore the difference between the α and β formulations for estimating latent heat flux. The derivation of the specific function relating α or β to θ is secondary since it is strictly applicable to the field soil (Yolo silt loam.) For this reason we fit a simple exponential for α and β to our data. Greater effort in finding a functional form does not seem justified in light of our goal.

Although α and β are traditionally thought of as functions of soil moisture content alone, we will first investigate the possible relationship between α and the soil surface temperature. This approach is taken to show a possible reason for the poor performance of the Edlefsen and Andersen equation in prediction of evaporation. A regression of $\ln\alpha$ versus $1/T_{s,\mathrm{abs}}$ yields a reasonably good relationship (see Table 1), where $T_{s,\mathrm{abs}}$ is the absolute surface temperature, but the resulting predictions of LE are rather poor (see Fig. 1). There appears to be no systematic reason for the poor prediction of latent heat since $\alpha(T_s)$ does not perform as well as the $\alpha(\theta)$ function described below over the entire range of α. Although the graphical results are not shown, soil surface temperature is a poor choice of a field-measured variable for estimating β, and similarly yields poor evaporation estimation results. Since measured surface temperature and soil moisture content were found to be negatively correlated with correlation coefficient $r = -0.7$, not all of the poor performance of $\alpha(T_s)$ can be attributed to the different measurement depths of the microwave radiometer and the IRT.

We next explore the effect of surface soil moisture as measured by the L- and S-band radiometers. The values of α and β calculated from (3) and (4) using the measured values of E, q_s^*, q_a, H, and u_* are shown plotted against the L- and S-band measurements of soil moisture in Figs. 2 and 3, respectively. Also shown on these graphs are the best-fit exponential curves describing the α–θ and β–θ relationships [α or $\beta = a \exp(b\theta)$]. The absence of any data points in the soil moisture content range from 0.10 to 0.19 is due to the failure of the micrometeorological station for DOY 170 and 171, as mentioned earlier. Nevertheless, it can be expected that the fitted curves should describe the missing data well. Regression statistics for the fitted lines are given in Table 2. (The variables were first log-transformed

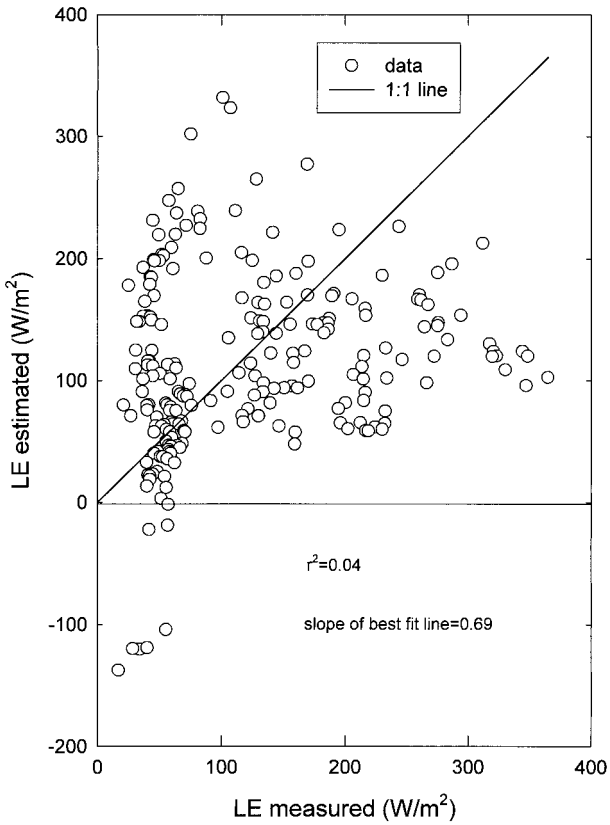

FIG. 1. LE estimated using the $\alpha - T_s$ exponential regression vs measured LE.

before regression, so that the statistics in Table 2 are for the relationship $\ln\alpha$ or $\ln\beta = a + b\theta$.) In the interest of brevity, because the deeper measurement depth of the L-band radiometer gives a slightly larger range of soil moisture values during the dry time, we have chosen to use these soil moisture values in the further analysis. Similar overall results were obtained using the S-band measurements.

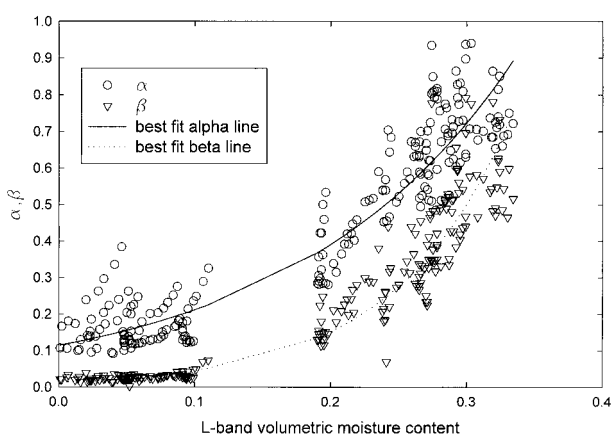

FIG. 2. Calculated α and β values vs soil moisture measured by the L-band passive radiometer (5-cm penetration depth).

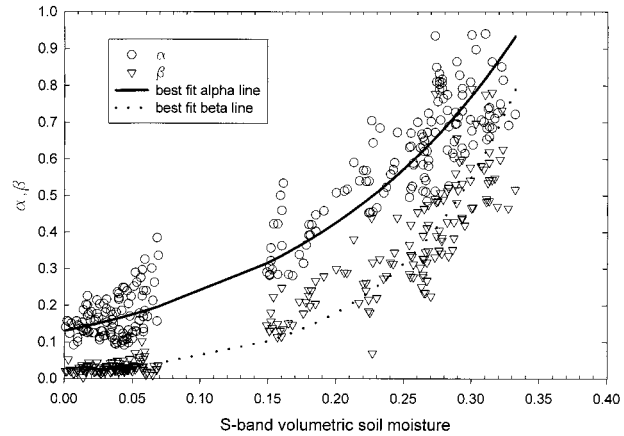

FIG. 3. Calculated α and β values vs soil moisture measured by the S-band passive radiometer (2-cm penetration depth).

The amount of error in the α and β values can be compared from the propagation of the measurement errors (Bevington and Robinson 1992). An approximate relationship between the amount of uncertainty δ_α in a given calculated α value and the uncertainty δ_β in the β value for the same time period is

$$\delta_\alpha \approx \frac{q_s^* - q_a}{q_s^*}\delta_\beta. \tag{8}$$

Since the measured values of $(q_s^* - q_a)/q_s^*$ ranged from 0.9 to 0.3, δ_α and δ_β will be approximately equal for each time period. This near equality of uncertainty implies that any differences in the results from using α or β are not due to greater inaccuracy of one of the parameters.

One of the most evident differences between the α and β values at dry soil moisture contents on both figures is that while the β values fall neatly in a line, the α values exhibit significant scatter. The scatter in α clearly follows a diurnal pattern. Figure 4 shows the α values of Fig. 2, with lines added to connect data points on the same day. Note that when the soil is relatively wet, α varies cyclically. The α values are lowest at midday and roughly the same early in the morning and later in the afternoon/early evening. This cyclic variation does not occur for α during the dry days; α decreases from the morning value and remains at a lower

TABLE 2. Regression statistics for the best-fit exponential functions for α and β as a function of θ in Figs. 1 and 2. The statistics are for the log-transformed linear regression of $\ln\alpha$ or $\ln\beta = a + b\theta$.

	L-band θ		S-band θ	
	$\ln\alpha$	$\ln\beta$	$\ln\alpha$	$\ln\beta$
Intercept	−2.17	−4.28	−2.04	−3.96
Std error of intercept	0.03	0.04	0.03	0.04
Slope	6.15	11.97	5.94	11.22
Std error of slope	0.15	0.20	0.13	0.21
r^2	0.88	0.94	0.89	0.92

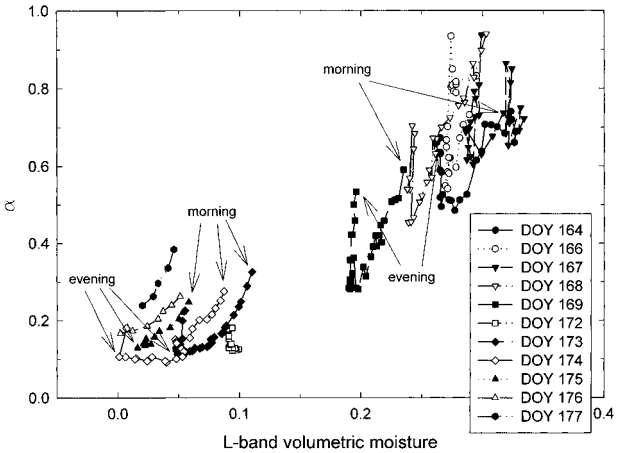

FIG. 4. Calculated α vs L-band volumetric soil moisture with values for individual days separated. The morning and evening endpoints of the daily time series of α for selected days are highlighted by the arrows. A diurnal cycle can be seen for the α time series of DOY 164 and 169, while for DOY 173, 174, and 175, the value of α in the late afternoon/evening does not return to its morning value.

value throughout the day. The fact that the amount of daily variation in α depends on the relative amount of soil moisture over the day may be useful in indicating whether the land surface is relatively ''wet'' or ''dry'' but also indicates that a single relationship linking α to soil moisture is difficult to form.

The variation in α over the course of the day can be compared to the behavior of the calculated value of β throughout the day, especially for the dry days. Examining Table 3, note that while the amount of variation in the β values during the wet days is roughly the same as the amount of variation in the α values (sum of squared error of 1.27 vs 1.40), there is strikingly little variation in β during the dry days both compared to the amount of variation in α during the dry days and compared to the amount of variation in β during the wet days.

The latent heat estimated using the fitting exponential equations for α and β is shown in Figs. 5 and 6. While β yields predictions of LE that fall close to the 1:1 line with a reasonable variance r^2, the α method tends to overpredict the evaporation and has significantly more scatter than the β method. Especially striking is a large cloud of points above and below the 1:1 line at values of LE less than 100 W m^{-2}. These points occur entirely during the dry time period starting at DOY 172. The corresponding LE predictions given by the β method all fall very close to the 1:1 line.

TABLE 3. The total sum of squared error (SSE) between the measurements and the regression lines (both α and β) shown in Fig. 1 and amount of the total SSE contributed by the wet days and the dry days.

	α	β
Total SSE	1.73	1.27
Wet days (DOY 164–169)	1.40	1.26
Dry days (DOY 172–177)	0.33	0.01

TABLE 4. Comparison of the regression results for predicted vs measured LE, where predicted LE is derived from α (θ) or α [θ,(1/T_s)]. The addition of 1/T_s as a prognostic variable causes little change in the results.

	lnα vs θ	lnα vs θ and 1/T_s
r^2	0.58	0.52
rmse (W m^{-2})	91.9	66.9
Slope of best-fit line	1.10	0.91

It has been suggested that one can use Eqs. (1) and (2) to show that

$$\alpha = \beta + (1 - \beta)\frac{q_a}{q_s^*}, \tag{9}$$

which implies that when $q_a \ll q_s^*$, α should approach β, the difference between q_s^* and q_a approaches q_s^*, and the two resistance equations should yield the same evaporation result. In this experiment, however, the minimum value of q_a/q_s^* was approximately 0.1, during which times the values of α calculated from the data were 3–5 times the values of β. If the ratio q_a/q_s^* is given now by r, we have

$$\alpha q_s^* - rq_s^* = \beta(q_s^* - rq_s^*)$$

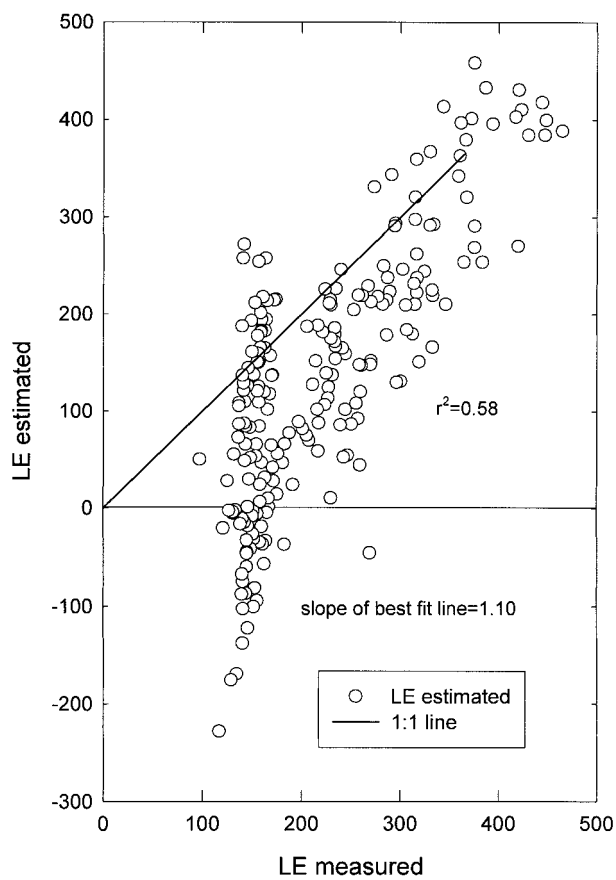

FIG. 5. LE estimated using the α − L-band soil moisture exponential regression vs measured LE.

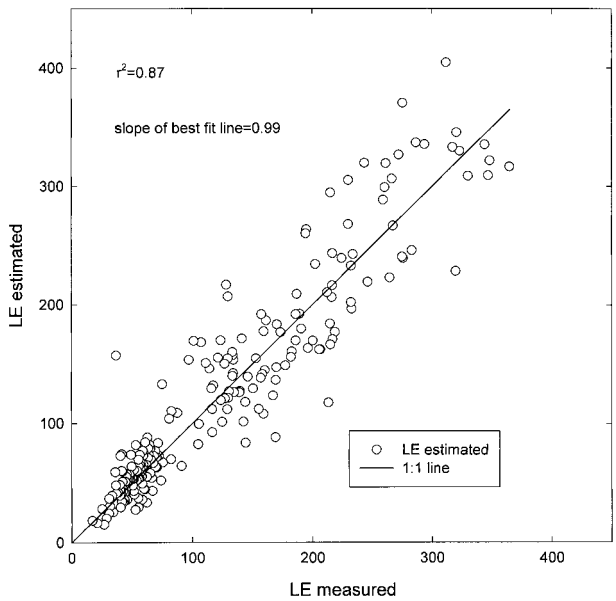

FIG. 6. LE estimated using the β − L-band soil moisture exponential regression vs measured LE.

and

$$\alpha - r = \beta - \beta r. \tag{10}$$

We can say $\alpha = \beta$ only if $r \ll \alpha$ and $\beta r \ll \beta$. Given that α ranges from 0.8 to 0.1 during the experiment, both of these conditions cannot be met. It is our opinion that the experiment at Davis provides a good test of any possible equality of the α and β methods since the low q_a and high q_s^* found in Davis in the summer yield perhaps as low a value of r as is to be found.

The amount of variation present in the α values during the dry days indicates that soil moisture content alone may not be a sufficient independent variable to model α. Additional prognostic variables can be postulated, such as the soil porosity (Ye and Pielke 1993). Examining (5), one might expect that porosity, T_s, and θ can be used together as prognostic variables (since ψ is directly related to θ and porosity). We are unable to investigate the effect of porosity on α and β in this study since we have data for only one soil. But because T_s is a poor prognostic variable for α, LE values predicted using the α formula from a combined regression of α versus θ and T_s are no better than LE obtained using $\alpha(\theta)$ alone, although the rms error is somewhat reduced. This implies that predicting the soil surface specific humidity is more complex than a simple function of θ and T_s.

4. Conclusions

Comparison of the evaporation estimates obtained by the α and β methods demonstrates that the β method yields superior results. Essentially β can be parameterized successfully by surface soil moisture alone, while α as a function of θ yielded less accurate estimates of evaporation. The inaccuracy of the α method is not due to greater sensitivity to experimental error, but rather because it attempts to model the specific humidity at the land surface, which is not trivial. The accuracy of the α method is not improved if surface temperature is included as a prognostic variable. Since the α approach is often applied when measurements of the land–atmosphere interface are not available, the consideration of additional prognostic variables for α seems counterproductive. We conclude that for scaling of the flux–gradient equation for evaporation estimation with near-surface soil moisture measurements, the β method is the most robust.

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