Scale issues in land–atmosphere interactions: implications for remote sensing of the surface energy balance

Nathaniel A. Brunsell a,∗, Robert R. Gillies b

a Department of Plants, Soils, and Biometeorology, Utah State University, Logan, UT 84322-4820, USA
b Department of Plants, Soils, and Biometeorology, and Department of Aquatic, Watershed and Earth Resources, Utah State University, Logan, UT 84322-4820, USA

Received 1 August 2002; received in revised form 15 January 2003; accepted 17 January 2003

Abstract

The interaction between the land surface and the atmosphere is discussed focusing on the recent literature. Of primary importance is the issue of scale and the variation across different levels of pixel resolution for using remotely sensed data in the determination of the different components of the surface energy balance (SEB). This leads into a discussion of various methods of aggregating local scale input parameters in order to calculate larger scale surface fluxes. As an example application, airborne and satellite data are coupled to a soil-vegetation–atmosphere-transfer (SVAT) model and applied to the Southern Great Plains 1997 (SGP97) Hydrology Experiment. A physically based aggregation scheme is suggested for radiometric temperature by decomposing the temperature into vegetation and soil components and then aggregating the radiance field based on the percent cover of vegetation. Fluxes derived from the airborne data agree well with those measured with eddy covariance stations. Satellite data agrees poorly with the surface and airborne estimates. However, after aggregating the airborne data to the resolution of the satellite, the agreement is better. This suggests that the satellite data is useful at estimating the fluxes at the 1 km² scale, while the comparison between the 1 km² satellite and the surface data may be problematic at such scales.

Keywords: Scaling; SGP97; Length scales; Surface energy balance

1. Introduction

Land–atmosphere interactions are currently treated simplistically in coarse resolution modeling schemes, given the complexity and inaccuracies of representing surface variability at such scales in a physically meaningful way. Therefore, for global climate and other models running with grids on the order of hundreds of km², it becomes necessary to greatly simplify or simply ignore many of the small scale interactions. In many cases, however, it is precisely the interactions on smaller scales that are important issues that need to be considered if one is to determine the large scale representative value for a model estimate.

An approach for approximating the complex nature of land–atmosphere interactions is to use remote sensing techniques to measure the radiative balance at a variety of resolutions. Major limitations to this approach include issues relating to the scaling of the satellite measurements and associated models. This introduces problems with (a) the comparison of measurements at varying scales and (b) issues related to the aggregation of both measurements and models. In many cases, the scientific objective of collecting surface measurements
of land–atmosphere interactions is to make some statement concerning the larger scale interactions within the region of study. This objective is a different aspect of the aggregation problem, i.e. how does one translate local measurements to make any conclusions concerning larger scale interactions? The use of remote sensing provides a possible methodology for quantifying the heterogeneity of the surface, as well as measuring the results of the interactions (i.e. the radiative balance) at a variety of scales. However, at the present time, there is no clear methodology for either validating remote sensing estimates with surface measurements, or for aggregating the satellite estimates to larger resolutions for input and/or validation of larger scale models.

Soil-vegetation–atmosphere-transfer (SVAT) models are developed to run at the homogeneous “patch” scale. The issue of heterogeneity within a SVAT model has been discussed previously (e.g. Giorgi and Avissar, 1997; Kustas and Jackson, 1999). Many studies have examined the issue of deriving areal average fluxes (i.e. at the pixel scale, Cracknell, 1998) from remotely sensed data with the use of a SVAT model. Many of these have been quite successful when compared to surface observations collected at the time of satellite or airplane overpass (e.g. Kustas et al., 2001). Other studies (e.g. Shuttleworth et al., 1997; Arain et al., 1999) have had reasonable results with coupling a SVAT model and remotely sensed land-cover data with a global climate model (GCM) to update the GCM with remotely sensed measurements. It appears that if the surface heterogeneity is minor, i.e. there are large patches (on the order of km²) that are relatively homogeneous, then the effects of aggregation may be relatively minor. This helps to explain why many field campaigns (e.g. HAPEX-MOBILHY, FIFE, and Monsoon’90) resulted in studies where the errors associated with linear averaging were minor. In cases where the variability tends to be large, the errors associated with linear averaging may increase due to the effects of non-linearities (i.e. feedbacks) in the surface energy balance (SEB).

A number of issues associated with these non-linearities are examined in this paper drawing on data from the Southern Great Plains 1997 (SGP97) Hydrology Experiment. SGP97 was a multidisciplinary experiment conducted in central Oklahoma in the summer of 1997. The general motivation of the project was to examine the spatial variability in soil moisture with the use of microwave remote sensing. To support the microwave data collection, a variety of complementary surface and remotely sensed data were collected. This provided one of the largest collections of data at a variety of scales and made available to the scientific community involved with using remotely sensed data to estimate the surface energy balance.

Before presenting such scale representations for the SGP97 data, it is worthwhile at this point to review some of the governing processes involved in land–atmosphere interactions. Specifically, the focus will be on the processes which directly influence the ability to use remotely sensed data for the estimation of the surface energy balance components with the aid of SVAT models. Following that, methods for aggregating local scale variables to larger scales are discussed and the inherent non-linearities of the surface energy balance are used to demonstrate why linear averaging should not work theoretically. A test application to SGP97 is discussed, after which some discussion is presented on the current state of understanding in scaling of the surface energy balance.

2. Non-linearity and the surface energy balance

The surface energy balance describes the interaction of many processes which occur at the land–atmosphere interface. The general approach to studying the SEB is to use a relatively homogeneous area on the order of tens of meters. The theoretical equations, parameters and variables are all well defined at this scale. However, this does not consider larger scale processes, i.e. the errors associated with the non-linearities are small and can generally be hidden in the controlling parameters.

Many of the problems associated with non-linearity are due to the influx of heat, moisture and momentum over heterogeneous areas. As the scale of interest is increased, the sources and sinks for the turbulent fluxes become discommensurate with the scales of the turbulent processes, thus, the flux may be against the local gradient, since the local gradient is not representative of the large scale turbulent transfer. If the flux is not proportional to the gradient, the assumptions underlying the micrometeorological theory for surface fluxes are violated and the theory is no longer valid.
One of the primary quantities used in the study of land–atmosphere interactions is the net radiation ($R_n$) (W m$^{-2}$). This is the energy available to do work at the surface. It is the difference between incoming and outgoing radiation:

$$R_n = (1 - a)R_s + \epsilon(L_a - \sigma T_s^4)$$  \hspace{1cm} (1)

where $a$ is the surface albedo (dimensionless), $R_s$ is the incoming solar radiation (W m$^{-2}$), $\epsilon$ is the emissivity of the surface (dimensionless), $L_a$ is the atmospherically emitted downwelled radiation (W m$^{-2}$), $\sigma$ is the Stefan–Boltzmann constant (W m$^{-2}$ K$^{-4}$) and $T_s$ is the surface temperature (K).

This is referred to as the “Aerodynamic resistance” method. It begins with the logarithmic profile for mean windspeed as a function of height as follows:

$$u(z) = u(z_0) \ln \left( \frac{z}{z_0} \right)$$  \hspace{1cm} (2)

where the wind stress (kg s$^{-2}$ m$^{-1}$) and $\rho$ is the density of the air (kg m$^{-3}$), where the prime signifies deviation from the temporal mean, thus $u_w'$ is the temporal covariance between the vertical and horizontal windspeed fields with the coordinate system oriented along the direction of the surface stress.

Adopting an aerodynamic resistance formulation for the transfer of the momentum, heat, and water vapor, the fluxes can be represented as:

$$\tau = \rho \frac{u_w'(z)}{r(z)}$$  \hspace{1cm} (3)

$$H = -\rho (q_h' - q_w') \frac{H(z)}{r(z)}$$  \hspace{1cm} (4)

$$E = -\rho (q_h' - q_w') \frac{E(z)}{r(z)}$$  \hspace{1cm} (5)

where $\rho$ is the density of air, $c_p$ is the specific heat capacity of air (J kg$^{-1}$ K$^{-1}$), $T_h$ is the aerodynamic temperature (K), $T_w$ is the air temperature (K), $q_h$ is the aerodynamic humidity (g kg$^{-1}$), $q_w$ is the humidity of the air (g kg$^{-1}$), and $r(z)$ are the aerodynamic resistances to momentum, heat, and water vapor transfer, respectively and are defined as functions of height as follows:

$$r(z) = \frac{1}{k_n(z)} \left( \ln \left( \frac{z}{z_0} \right) - \psi M(z) \right)^2$$  \hspace{1cm} (6)

$$r_h(z) = \frac{1}{k_n(z)} \left( \ln \left( \frac{z}{z_0} \right) - \psi h(z) \right)$$  \hspace{1cm} (7)

$$r_e(z) = \frac{1}{k_n(z)} \left( \ln \left( \frac{z}{z_0} \right) - \psi e(z) \right)$$  \hspace{1cm} (8)

where $L$ is the Obukhov length (m):

$$L = -\frac{u_w'(z_0)}{k_n(z_0) \frac{\theta}{g \theta h}}$$  \hspace{1cm} (9)

and $\theta$ is the virtual potential temperature (K), $g$ is acceleration due to gravity (m s$^{-2}$), and the $\psi$ terms are stability corrections to the logarithmic profiles valid in neutral atmospheric conditions.
Eq. (8) represents the resistance to momentum transfer from the atmosphere down to the roughness length for momentum $z_0$. For a horizontally homogeneous flat surface in neutral conditions, the roughness length for momentum is defined as the height above which a logarithmic profile in mean wind speed is observed. Analogously, the resistance terms are defined for heat and water vapor into the atmosphere. The roughness heights for heat and water vapor are the heights above which similarity theory applies for temperature and humidity. For homogeneous surfaces, these heights are well defined and represent the sink for turbulent momentum flux and the effective source for turbulent heat and water vapor fluxes. However, for heterogeneous surfaces these are taken as non-constant effective parameters so that Monin-Obukhov similarity theory can be applied.

3. Remotely sensed estimation of turbulent fluxes

In terms of the remote sensing of the surface energy balance, the primary focus has been on the determination of the sensible heat flux. The primary reason for this is the premise of spatially distributed radiometric surface temperature fields. This approach has met with difficulty due to the fact that the source of the sensible heat transfer is $z_{fr},$ and not the surface. This quantity cannot be measured with satellites. What can be measured is the radiometric temperature, which is a composite temperature of all the elements within the pixel. In order to use a formulation such as Eq. (6), it is necessary to relate the aerodynamic temperature with the radiometric temperature. Furthermore, there are complications related to estimating the resistance terms on a pixel basis. Measuring surface fluxes with the eddy covariance technique results in measurements of the flux without knowledge of the resistance and roughness lengths. However, when estimating the flux with remote sensing it is not an independent measurement of the flux, and knowledge of the resistance terms becomes a necessary component to estimating the flux.

Some studies have attempted to use Eq. (6) by simply replacing the aerodynamic temperature with the radiometric temperature and adding an additional resistance term called the “excess” or “radiometric” resistance which accounts for the resistance to flow from the surface up to the roughness height where the aerodynamic temperature is measured. An additional complication is the fact that many researchers replace $r_s$ with $r_s$, where $r_s$ is also termed an “excess” resistance. This is done since the resistance to momentum is easier to calculate from field data by extrapolation of the wind profile. In this case it is useful to define a parameter $kB^{-1}$:

$$kB^{-1} = \ln \frac{\Delta \theta}{\Delta \theta_e} = k u^* r_s$$

Studies (e.g. Kustas and Jackson, 1999; Kustas et al., 1989) that have examined the variability in $kB^{-1}$ parameter as functions of canopy conditions (leaf area index (LAI), height, and fractional cover), water stress (soil and canopy moisture levels), as well as environmental variables (vapor pressure deficit and wind speed), and concluded that since the parameter is so variable, it is not the best way to estimate sensible heat using radiometric temperature in areas that are sparsely vegetated. Sun and Mahrt (1995a) investigated the relationship between aerodynamic and radiometric temperatures within the framework of traditional similarity theory. They attempted to define a “radiometric roughness length” for heat ($z_{fr}$) given as:

$$\ln (z_{fr}) = \ln (\psi_0) + \frac{k \Delta \theta}{\theta_e} - \psi_0 \left( \frac{z}{\bar{z}} \right)$$

where $\Delta \theta = \theta_e - \theta(z)$ represents the difference in potential temperatures determined from the radiometric temperature $\theta_e$ and that measured at height $z,$ and $\bar{z}$ is the turbulent scale for temperature defined as $\delta_1 = \frac{\bar{z}^2}{r_s}$. They found that the formulation for the radiometric roughness length is outweighed by the large differences in radiometric and air temperatures. Moreover, they found that values of $z_{fr}$ were extremely small and have little physical meaning, and simply represent a “tuning” to correct for the incorrect usage of the radiometric temperature. They also came to the conclusion that the reason that the $kB^{-1}$ parameter has worked is due to the relationship between

$$z_{fr} = z_0 + D$$

where $D$ is the land surface characteristic length scale, which is approximately equal to the surface roughness length $z_0.$
and not to any relationship between the roughness lengths for momentum and radiometric roughness lengths. They concluded that the $k_B^{-1}$ parameter is not a valid approach for estimating the sensible heat flux to the radiometric temperature.

Recent studies (e.g. Hasager and Jensen, 1999; Schaudt and Dickinson, 2000) have attempted to estimate spatial distributions in roughness length for momentum from remotely sensed data. Hasager and Jensen (1999) used a land-cover classification and linearized flow equations coupled with a "microscale aggregation model". The results indicated good agreement to first order based on simple land-cover types. However, as they note, this is only a first approximation as $z_0$ changes throughout the year even within the same field. Schaudt and Dickinson (2000) followed a similar approach, although they based their estimates on vegetation indices and estimated roughness length and displacement heights as a ratio of canopy height. Their method requires some input that is not available on a global basis, e.g. crown aspect ratio and canopy density. Again, as a first order approximation, this method is acceptable. It should be pointed out though, that calculations based on surface measurements are highly variable for roughness lengths and are not constant even for a single day. Therefore, given the present state of understanding concerning these quantities, even having an approximation good to first order is quite an achievement.

Other studies have attempted to calculate site specific coefficients which are used with Eq. (6) to account for the differences between radiometric, aerodynamic and air temperatures. Chehbouni et al. (1997, 2000) developed such a relationship and associated the relationship with leaf area index measurements. This approach appears to be of limited use in terms of a universal solution to the problem and the measurements necessary for such an approach are not routinely taken. However, as discussed by Chehbouni et al. (1997) this may not be the case since the formulation developed for simulated data worked well in a few differing semi-arid areas; hence, they claim that the approach may be of general use. Further research is necessary to determine how universal the approach is, and for what vegetation conditions in can be applied.

One issue that has only recently been given notice is the fact that a radiometer on board a satellite receives an instantaneous estimate of radiometric temperature (Kustas et al., 2002). Given the nature of turbulent fluxes, an estimate based on one instant may or may not be representative of the underlying conditions generating a temporal average of the flux. In their study, Kustas et al. (2002) compared flux estimates from a time series of radiometric temperature estimates over various temporal averaging lengths (e.g. 5, 10, and 30 min averages), and found the choice of the time average leads to significant deviations between remotely sensed estimates of the fluxes and those measured. Obviously, more study into this issue is necessary before any conclusion can be drawn concerning the feasibility of estimating fluxes with instantaneous remotely sensed measurements.

4. Surface heterogeneity

In terms of micrometeorological theory there is a clear distinction of whether or not the surface heterogeneity is significant: whether or not the surface variability is enough to cause changes in the atmospheric boundary layer (ABL). Shuttleworth (1988) distinguishes the two as "disorganized" or Type A, where the surface patches are too small to show an "organized" response to the ABL, and "organized" or Type B where the individual patches can alter the properties of the ABL. The distinction is often given as occurring on the order of 10 km$^2$.

Raupach and Finnigan (1995) developed a similar distinction. In this case, the microscale heterogeneity is on the order of 1–5 km$^2$, and is a function of the ABL height and the Deardorff velocity scale ($w^*$, m s$^{-1}$). Macroscale heterogeneity is on the order of 100 km$^2$ and is a function of the entrainment time scale, which represents the ability (or lack thereof) of the properties of the air to mix between patches as the ABL evolves and is accompanied by a time scale on the order of time since dawn. The scales between these two extremes (i.e. an intermediate case) is considered mesoscale heterogeneity and, as of yet, there is no clear method for determining the relationship between the ABL and surface variability. Thus, the issue is raised as to how large must surface patches be to have an effect on the properties of the ABL? This is an unanswered question, and undoubtedly depends upon not only the distribution of sizes of surface patches, but also the spatial configuration of the patches, the
properties of the ABL, time of day, and the magnitude of the surface fluxes, among many other things. As an example of the effects of the varying sizes of patches, consider large agricultural fields, with small areas of hot, dry regions. The effects on the resultant fluxes will obviously be different than if the wet and dry regions are represented in equal proportions. In order to consider spatial configuration effects, the possible differences between two large patches, one hot and dry with a large sensible heat flux, and the other being a wet, cool irrigated agricultural field. If the dry patch is upwind of the agricultural field, the resultant latent heat flux from the irrigated patch will be larger than if the dry patch was not upwind (this effect due to the advection from the dry patch).

An important concept when examining the issue of areal averaged fluxes is the blending height \( z_{\text{blend}} \) (Mason, 1988; Dolman and Blyth, 1997). This represents the height in the atmosphere above which the fluxes represent an areal average and are no longer affected by the location on the surface. Of course, in reality there is no clear height above which the effect of surface heterogeneity completely vanishes, and as discussed in Mahrt (2000), it more properly represents the decreasing influence of surface variability with height. Mahrt (2000) goes on to develop arguments, based on the order of magnitudes of the controlling variables (similar to those of Raupach and Finnigan (1995)), for a relationship between surface length scales and various atmospheric properties (e.g. intensity of turbulence \( u_* \)), mean wind speed, etc.). For the microscale case, he notes the following condition:

\[
L_{\text{hetero}} \ll C_{\text{blend}} U^2 u_* h
\]

where \( L_{\text{hetero}} \) (m) is the horizontal length scale of surface variability, \( C_{\text{blend}} \) (dimensionless) is a coefficient roughly 0.6 (Mahrt, 2000), \( U \) is the mean wind speed, \( u_* \) is the friction velocity, and \( h \) is the height of the atmospheric boundary layer (m).

When the condition in Eq. (14) is met, then the tile or “mosaic” approach (Koster and Suarez, 1992) to estimating areal average fluxes is valid. This approach consists of modeling the dominant land-cover types within a pixel independently and averaging the resultant flux. In microscale heterogeneity, the patches are too small to significantly influence the ABL, and therefore this approach works.

A different methodology for examining the effects of surface variability has evolved from the modeling community, specifically, the use of large eddy simulation (LES) models. Shen and Leclerc (1995) simulated sinusoidal length scales with various wavelengths as fractions of the ABL height. Albertson and Parlange (1999a,b) investigated the effect that different length scales of surface variability had on momentum flux during neutral conditions. Perhaps of more consequence, they also examined the effects of smooth to rough versus rough to smooth transitions on the momentum flux. This has implications concerning the modeling of edge-effects on momentum flux (and hence, other turbulent fluxes) and the spatial configuration of the patches along the mean wind field. This model was recently extended (Albertson et al., 2001) to include remotely sensed data as a lower boundary condition and coupled with a SVAT model to estimate pixel level flux input into the LES.

5. Aggregation

The translation of measurements gathered at one resolution to a larger resolution is termed aggregation (sometimes termed “up-scaling”). In the case of land–atmosphere interactions, as mentioned previously, this is a non-trivial issue due to the many non-linearities associated with the measurements and parameters. For the case of specificity, the issue of flux aggregation will be discussed here.

Linear averaging can be used if there is a conservation law (mass or energy) associated with the quantity being aggregated and the associated non-linearities of the system are small enough that they can be neglected (Giorgi and Avisar, 1997). Hence, surface energy fluxes can be linearly averaged due to the conservation of energy. However, this requires the knowledge of all the fluxes at all of the points in the region under examination. Thus, the areal average flux is defined as:

\[
F = \sum \alpha_i f_i
\]

where \( \alpha_i \) is the fractional area contributing flux \( f_i \), and \( F \) is the true areal averaged flux.

However, as stated earlier, the application of Eq. (15) requires knowledge of the fluxes at all points. This is not feasible due to measurement requirements.
It is often convenient to assume (Raupach and Finnigan, 1995) that the model formulation for large scale fluxes has the same form as that developed at the small scale, and it is only necessary to define the correct average for the input parameters. Thus, if $f(x)$ represents the local formulation for a flux as a function of small scale inputs $x$, then the areal average flux as a function of large scale inputs is given by $F(\bar{X})$.

However, the application of such a methodology is problematic if the form of the model is not linear, in which case:

$$F = f(x) \neq F(\bar{X}) \quad (16)$$

The true areal averaged flux is the average of all the local scale formulations, however this is not equivalent to the large scale formulation with the average of the input variables. Of note, however, is the fact that the conservation laws associated with fluxes (i.e. linear averaging) do not extend to those parameters (e.g. resistance terms) that determine the local scale fluxes. Thus, it is necessary to examine the issue of aggregation. There are two primary methodologies for approaching the aggregation problem, by representing surface properties in either a discrete or a continuous fashion.

### 5.1. Discrete methods of aggregation

The first is to approximate the surface as a finite number of discrete, homogeneous patches. Fluxes are calculated for each patch, and then averaged. Koster and Suarez (1992) used a discrete approximation when developing the “mosaic” or tile approach, where each patch is for the most part independent of all other patches, and only affect one another through the mutual determination of boundary layer properties. As discussed previously, this method is only applicable for microscale heterogeneity (Mahrt, 2000), due to the necessity that each patch must be independent of each other in terms of energy transfer.

As the surface heterogeneity moves to mesoscale variability, a more appropriate discrete method may be the use of effective parameters (for a recent review of the effective parameters approach, the reader is referred to Hu et al. (1999)). This approach attempts to calculate the averaged value of the flux by determining the appropriate value of the necessary parameters. Thus, it assumes that the patch level formulations for each component of the energy balance can be used at the larger scale, as long as the correct values for parameters are derived. More importantly, it basically assumes that all non-linearities and heterogeneities within the system can be neglected provided you choose the “right” scale where the effective parameters are valid.

The most widely used method of deriving the necessary formulations for determining the effective parameters is through “flux matching.” This requires, at the very least, that the flux calculated at the large scale is the linear average of all patch level fluxes. Other requirements are often placed in addition to this, including energy balance closure at all scales, linear averaging of radiometric surface temperature, etc.

The primary problems with the effective parameters approach is that they often require site specific calibration coefficients and therefore are of limited applicability. Moreover, many researchers have found that the parameters generated by “flux matching” are not unique and that different formulations are needed for the same terms; depending on which flux one is attempting to calculate (Lhomme et al., 1994).

### 5.2. Continuous methods of aggregation

A different approach to the aggregation problem is to approximate some or all of the parameters with a continuous probability density function (p.d.f.) (e.g. Li and Avissar, 1994). This approach requires the integration (by either analytical or numerical methods) of the appropriate equations over the p.d.f. of the input parameters. A problem with this method is the increase in computational time needed as the number of parameters represented by p.d.f. increases. In addition, the determination of the p.d.f. can be arbitrary.

An example of the use of p.d.f. can be found in Li and Avissar (1994), who used the Patchy Land–Atmosphere Interactive Dynamics (PLAID) model to examine the effect of different distribution types of five controlling variables: stomatal conductance, surface moisture, leaf area index, surface roughness and albedo. They found that the spatial variability most directly effects the latent heat flux and by just using the mean of these variables results in large errors in LE. Giorgi (1997a) used p.d.f. for surface temperature and soil moisture to model the spatial heterogeneity of the surface. The model treatment between the statistical
approximations were considered to be independent of one another, but the model performed well in the validation work presented in Giorgi (1997b).

5.3. Spatial configuration

None of the above methods (either discrete or continuous) make any attempt to deal with variations in the spatial configuration of the patches. In general, the methods neglect any feedbacks which accompany the spatial orientation rather than merely the p.d.f. or the effective orientation. Many of the problems associated with non-linearities in the surface energy balance are directly attributable to the spatial configuration of patches on the landscape. Take, for example, a hot dry bare soil area directly upwind of a irrigated agricultural field. In this case, advection of vapor pressure deficit and sensible heat flux will result in higher evaporation rates from the field than would be achieved in a single homogeneous field. By partitioning the landscape into distinct land-cover types and treating each as independent of one another, such effects are completely ignored.

6. Estimation of the SEB via SVAT modeling

One approach that is often used in the estimation of the SEB via remote sensing data is to couple the remotely sensed estimates (e.g. radiometric temperature and vegetation indices) with a SVAT model (Friedl, 2002). In order to use this approach, a variety of surface and atmospheric measurements are needed at the time (or the morning) of the remote measurements. These measurements are used to drive the model up to the time of the overpass.

Before progressing, it should be noted that estimating the components of the SEB with a SVAT model directly at the scale of remote sensing bypasses the aggregation problem by inherently assuming that the patch level formulations are directly applicable at the resolution of the remotely sensed data (i.e. it assumes microscale variability). This method, although quite successful in some applications, does not provide a theoretical basis with which to understand the true effects of surface heterogeneity on the SEB.

The generalized methodology that is used is generically called the “two-source” (Norman et al., 1995) approach. This breaks up the pixel into a component system in which the land–atmosphere interactions are determined by the vegetated and the bare soil portions. Therefore, the pixel scale flux is:

\[ F = F_v \cdot F_v + (1 - F_v) \cdot F_s \]  

(17)

where \( F \) is the resultant pixel scale flux, and \( F_v \) and \( F_s \) are the fluxes determined by the vegetation and soil respectively, and \( F_v \) is the percent cover of vegetation. The component fluxes are usually independent of each other, except for the resultant modification of the atmospheric properties above them, which they both influence and the response to which partially determines the flux.

Practically, the determination of the flux from remotely sensed data is usually done by inverse modeling. The level of vegetation and other parameters (including soil moisture) are prescribed for each run. At the time of the overpass, the fluxes are output from the model. This process is iterated over the entire possible range of vegetation and soil moisture values and a regression is constructed based on the radiometric temperature and amount of vegetation (percent cover) present within a pixel.

Several studies (e.g. Gillies and Carlson, 1995; Gillies et al., 1997; Moran et al., 1997) have noticed a triangular shape is achieved when a remotely sensed vegetation index (e.g. NDVI or fractional vegetation (Fr)) is plotted against the radiometric temperature (Fig. 1). The variation along the base of the triangle (bare soil) is assumed to represent the combined effects of soil moisture and topography. The right most side of the triangle represents the warmest pixels through the range of vegetation, and is assumed to represent the pixels with no moisture in the top layer of the soil. The left side of the triangle represents the cooler pixels which are assumed to be saturated in the top layer of soil. Thus, if the image data contains areas that range from bare soil to full vegetation, and from 0 to 100% relative soil moisture availability and surface measurements are reliable, there should be little problem with this methodology.

However, several problems do exist with this method. One problem which is often confronted within this approach is the applicability of the surface measurements to the entire domain of the remote sensing measurements. This is a “representativeness” problem, in the sense that surface measurements are
often collected in a region of limited heterogeneity so that the equations of the SEB are known to be applicable.

In addition to the “representativeness” problem, an additional problem is encountered with the level of complexity within SVAT models. Many of the parameters and measurements that are needed to run these models are not routinely collected. Some have little (if any) physical significance when applied to the resolution of a satellite pixel. Many studies have shown that regardless of the level of complexity within a model, they often perform very poorly if not properly calibrated to the specific site. This “calibration” often requires the educated guess of many important, but not specifically defined parameters at the scale of application.

A more subtle and theoretical problem is the issue that the bare soil and vegetated components of the surface may not be contributing equally (a) to the fluxes or (b) to the average radiometric temperature according to the fractional cover. This issue was examined by Sun and Mahrt (1995b). They compared simple estimates of sensible heat flux calculated by the average radiometric temperature and using microscale variations in radiometric temperature and calculating the flux based on cover type (bare soil or vegetation). The use of the average radiometric temperature resulted in a negative heat flux due to shaded, moist areas. Using the microscale variations and the surface cover type resulted in the flux being in the proper direction. This has implications for the estimation of the flux when only one temperature is available at the large resolution common to satellite remote sensing.

Even considering these problems, many feel that this is the best approach for estimating surface energy fluxes from remotely sensed data. This is due to the fact that with proper calibration, many of these models are quite successful at reproducing observed fluxes.
7. Application to SGP97

An application of some of the concepts explained in this paper is now developed for the Southern Great Plains 1997 Hydrology Experiment. Two resolutions of remotely sensed data were used (12 m airborne and 1000 m satellite). These data are corrected for atmospheric effects and coupled to a SVAT model to estimate the surface energy balance on a pixel basis. Four eddy covariance stations within the El Reno study area were used for comparison purposes between the remotely sensed estimates and the surface measurements. An aggregation scheme is proposed and tested for translating the high resolution airborne imagery to that of the AVHRR satellite.

A brief overview of the data used in this research is given first, followed by an in-depth discussion of data correction and various aspects of scale and spatial heterogeneity. The remotely sensed data used here is from both airborne and satellite sources. The airborne data consists of the overpass conducted on July 2, 1997 over the El Reno intensive study area at approximately 10 a.m. CST. The Thermal Mapper Simulator (TMS) near-infrared and red bands were used at 12 m resolution. The thermal airborne data is from the Thermal Infrared Multispectral Scanner (TIMS) flown with the TMS and also at 12 m pixel resolution. The satellite data used here consists of the AVHRR overpass also on July 2, 1997 collected at approximately 2 p.m. Three bands were used from the five-band data at 1000 m resolution; the red, near-infrared, and band 4 for the thermal information. The surface data consisted of four eddy covariance stations from which measurements of the surface energy balance fluxes were obtained. Additional surface data used from the stations includes wind direction, air temperature, and friction velocity ($u^*$).

7.1. Visible and near-infrared data correction

The at-sensor radiance in the near-infrared and red bands were atmospherically corrected using Modtran 3 (Kneizys et al., 1996) and local radiosonde data in order to obtain surface reflectance values in those bands for both TMS and AVHRR.

Modtran is initialized with the radiosonde profile and is iterated over surface reflectance values $R_{sfc}$ in increments of 0.1, and over all scan angles ($\theta$, in increments of 5°) observed within the image. The scan angle is used as an approximate measure for path length through the atmosphere. Due to scattering effects, the asymmetry between east and west of nadir was taken into account.

The calculations from Modtran include an integrated radiance over the wavelength of interest (in this case, the spectral wavelengths of each sensor band). These values are used to develop a regression of the form:

$$R_{dc} = a_1 + a_2 \theta + a_3 \theta R_a$$  \hspace{1cm} (18)

which relates surface reflectance to apparent radiance ($R_a$, W m$^{-2}$), the pixel value of the remote sensing data and the sensor scan angle $\theta$, and the $a_i$ terms represent the regression coefficients.

The atmospherically corrected surface reflectance values were used to calculate the Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{\rho_2 - \rho_1}{\rho_2 + \rho_1}$$  \hspace{1cm} (19)

where $\rho_1$ is the reflectance in the red and $\rho_2$ is the reflectance in the near-infrared band. Gillies et al. (1997) developed the fractional vegetation (Fr) as the percentage of vegetation observed within a pixel as:

$$Fr = \left( \frac{NDVI - NDVI_{v}}{NDVI_{s} - NDVI_{v}} \right)^2$$  \hspace{1cm} (20)

where $NDVI_s$ and $NDVI_v$ are the bare soil and fully vegetated NDVI values.

7.2. Thermal data correction

The six-band TIMS and band 4 of AVHRR were corrected to temperature via Brunsell and Gillies (2002) which incorporates the surface emissivity calculated as a linear interpolation between bare soil and fully vegetated emissivity values:

$$\bar{\epsilon} = \epsilon_s \cdot Fr + \epsilon_v \cdot (1 - Fr)$$  \hspace{1cm} (21)

where $\epsilon_v$ was taken to be 0.985 and $\epsilon_s = 0.955$ (Schmugge, personal communication).

To obtain surface temperature values from the six-band TIMS data, radiometric temperatures in each band were converted to radiance values. These six values were then fit with a fourth order polynomial
which represents the variation in radiance as a function of wavelength over the thermal portion of the spectrum for that pixel. The wavelength corresponding to the maximum radiance (i.e. the inflection point of the polynomial) was inverted using Wien’s law to calculate the surface radiometric temperature of the pixel.

In order to compare the airborne data with AVHRR data it was necessary to model the fluxes at the same time of day. The airborne data was collected shortly after 10 a.m. local time, while the AVHRR overpass was at 2 p.m. Therefore, the SVAT model was used to derive a linear relationship between the 10 a.m. and the 2 p.m. radiometric surface temperatures (Fig. 2) by holding all parameters constant and relating the 10 a.m. and 2 p.m. radiometric temperatures of an environment with the same values of fractional vegetation and soil moisture availability. Fluxes were then computed from the 2 p.m. temperatures for comparison to the AVHRR data.

7.3. Derivation of surface fluxes

A SVAT model (Gillies, 1994) was used to determine the variability of model derived energy fluxes as a function of the relative soil moisture ($M_0$) and fractional vegetation ($Fr$). The relative soil moisture is the ratio of actual to potential evaporation (Gillies et al., 1997). In order to calibrate the SVAT model, a process of matching the extreme values of fractional vegetation and temperature was used. In the vegetation-temperature space, parameters were adjusted until the four corners were matched by the model to the observed remotely sensed data (Fig. 3). These corners consist of the values ($Fr = 0.0, M_0 = 0.0$), ($Fr = 1.0, M_0 = 0.0$), ($Fr = 0.0, M_0 = 1.0$), and ($Fr = 1.0, M_0 = 1.0$) with the value of radiometric temperature being the criteria for matching.

Once the model and remotely sensed data agreed for temperature values, the model was iterated over all values of $M_0$ and $Fr$ in order to determine the fluxes at

![Fig. 2. Relationship between radiometric temperature at 10 a.m. vs. 2 p.m.](image)
2 p.m. Following the model runs, a regression was established which related the observed temperature and fractional vegetation to the resultant flux estimated from the calibrated SVAT model:

$$F_x = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{i,j} T_i F_r^j$$

(22)

where $F_x$ is the predicted value of the pixel scale flux and $a_{i,j}$ are the regression coefficients.

7.4. Comparison with surface measurements

The comparison of remotely sensed measurements with surface measurements is not a trivial task. This is due to discrepancies between the footprint of the surface flux station and the pixel size of the remotely sensed data. Therefore, two schemes were chosen to assess the accuracy of the SVAT derived fluxes for the TMS/TIMS derived data:

1. pixel-wise comparison;
2. estimating the footprint of the station via the algorithm of Schuepp et al. (1990).

Pixel-wise comparisons are tenuous for several reasons. Primarily, it has been shown that the largest contribution to measured fluxes can be on the order of 50 m upwind of the station. Thus, for pixel sizes less than that size, pixel-wise comparisons will miss the dominant source of the measured flux. However, for larger pixel sizes such as the AVHRR sensor, there is often little else one can do.

The algorithm of Schuepp et al. (1990) accounts for the differences in contributed flux as a fluctuation of the upwind distance and the friction velocity:

$$\text{CNF}(x_L) = e^{-u(z-d)/u_k x_L}$$

(23)

where CNF is the normalized contribution to the flux measured at height $z$ (m), $x_L$ is the upwind distance from the measurement location (m), $d$ is the zero-plane displacement (m), and all other terms are as defined previously. Estimating the contribution of the upwind...
Table 1
RMS errors (W m\(^{-2}\)) for comparison of remotely derived sensible and latent heat fluxes compared to surface measurements for different methods of comparison

<table>
<thead>
<tr>
<th>Source</th>
<th>Compared Method</th>
<th>H</th>
<th>RMSE/H</th>
<th>LE</th>
<th>RMSE/LE</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMS/TIMS</td>
<td>Surface Pixel-wise</td>
<td>18</td>
<td>0.16</td>
<td>43</td>
<td>0.15</td>
</tr>
<tr>
<td>TMS/TIMS</td>
<td>Surface Schuepp</td>
<td>37</td>
<td>0.32</td>
<td>80</td>
<td>0.27</td>
</tr>
<tr>
<td>TMS/TIMS 1080a</td>
<td>Surface Pixel-wise</td>
<td>90</td>
<td>0.77</td>
<td>145</td>
<td>0.5</td>
</tr>
<tr>
<td>TMS/TIMS 1080b</td>
<td>Surface Pixel-wise</td>
<td>46</td>
<td>0.39</td>
<td>21</td>
<td>0.07</td>
</tr>
<tr>
<td>TMS/TIMS 1080a</td>
<td>Surface Pixel-wise</td>
<td>53</td>
<td>0.46</td>
<td>87</td>
<td>0.3</td>
</tr>
<tr>
<td>TMS/TIMS 1080a</td>
<td>Surface Pixel-wise</td>
<td>56</td>
<td>0.43</td>
<td>55</td>
<td>0.19</td>
</tr>
<tr>
<td>TMS/TIMS 1080b</td>
<td>Surface Pixel-wise</td>
<td>27</td>
<td>0.24</td>
<td>43</td>
<td>0.12</td>
</tr>
<tr>
<td>TMS/TIMS 1080c</td>
<td>Surface Pixel-wise</td>
<td>26</td>
<td>0.23</td>
<td>50</td>
<td>0.14</td>
</tr>
</tbody>
</table>

TMS/TIMS refers to fluxes derived from 12 m data. TMS/TIMS 1080 refers to aggregated fluxes to 1080 m for comparison to A VHRR via (a) linear averaging of 12 m flux values; (b) temperature and NDVI linearly averaged; (c) temperature and fractional vegetation linearly averaged; (d) temperature aggregated and fractional vegetation linearly averaged; and (e) temperature aggregated and NDVI linearly averaged.

The surface radiometric temperatures derived from the TIMS sensor were aggregated to the resolution of 1080 m for comparison with the AVHRR data for the extent of the airborne overpass. The aggregation of the vegetation indices of NDVI and Fr were discussed in Brunsell and Gillies (2003).

The aggregation scheme for radiometric temperature consists of assuming the pixel is a mixture of soil and vegetation cover. Separate regression equations were fit to determine the fully vegetated and bare soil temperatures as a function of SVAT modeled soil moisture (i.e., regression curves relating the radiometric temperature to soil moisture variability along the top (Fr = 1.0) and bottom (Fr = 0.0) of the triangle scatterplots):

\[ T_v = a_0 + a_1 M_v Fr = 1.0 \]  
\[ T_s = b_0 + b_1 M_s Fr = 0.0 \]

The pixel radiometric temperature was then decomposed into respective soil and vegetation temperatures using the fractional vegetation. The modeled soil moisture was assumed to be constant across the pixel, i.e., the same soil moisture value was applied to both the vegetated and bare soil component. Thus, following the soil moisture isopleths to the appropriate value along the Fr = 1.0 and Fr = 0.0 gives the respective component temperatures. For each pixel, the vegetation and bare soil temperatures were converted to radiance at the initial pixel resolution.

The fractional vegetation was calculated for the new resolution of 1080 m (see Brunsell and Gillies (2003) for discussion concerning the aggregation of vegetation indices) via aggregating the NDVI values from the initial resolution (in this case, 12 m). Using the aggregated value of fractional vegetation at the new resolution, the separate radiance values for the vegetation and soil components were then averaged based on the percent cover:

\[ \sigma \epsilon_i T^4 = Fr \sigma \epsilon_v T^4_v + (1 - Fr) \sigma \epsilon_s T^4_s \]

This involves the assumption that the component radiances are related linearly to the total radiance at the
Table 2 shows RMS errors between aggregated TMS/TIMS fluxes and the AVHRR fluxes. All comparisons are pixel-wise due to the large pixel area. The sensors are measuring an aggregation of radiance in which the radiance is linearly averaged over all components.

As a specific example of the various schemes, a closer look at the ER05 station is presented. Fig. 4 presents a histogram of the variability in fractional vegetation and radiometric temperature around the eddy covariance station. The actual histogram values correspond to the 12 m pixels from the TMS Fr and the TIMS radiometric temperatures. The vertical lines represent the pixel value containing the flux tower, as well as the aggregated values up to different levels of resolution including (a) 780 m, (b) 1080 m and (c) the value corresponding to the AVHRR sensor. Important things to notice concerning this data are (a) there is relatively little difference between the 12 m average and the aggregated values of the fractional vegetation data, suggesting that the field is relatively homogeneous with respect to vegetation cover (numbers of the aggregated and AVHRR values range from 0.74 to 0.83), and (b) this homogeneity does not carry over into the temperature field where the aggregated pixel temperatures are significantly higher than the average.

### Table 2

Comparison of flux aggregation schemes described in Table 1 between TMS/TIMS and AVHRR pixel-wise fluxes

<table>
<thead>
<tr>
<th>Source</th>
<th>Compared Method</th>
<th>H</th>
<th>RMSE/H</th>
<th>LE</th>
<th>RMSE/LE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVHRR</td>
<td>TMS/TIMS 1080a</td>
<td>Pixel-wise</td>
<td>41</td>
<td>0.35</td>
<td>130</td>
</tr>
<tr>
<td>AVHRR</td>
<td>TMS/TIMS 1080b</td>
<td>Pixel-wise</td>
<td>50</td>
<td>0.42</td>
<td>64</td>
</tr>
<tr>
<td>AVHRR</td>
<td>TMS/TIMS 1080c</td>
<td>Pixel-wise</td>
<td>58</td>
<td>0.49</td>
<td>125</td>
</tr>
<tr>
<td>AVHRR</td>
<td>TMS/TIMS 1080d</td>
<td>Pixel-wise</td>
<td>27</td>
<td>0.34</td>
<td>43</td>
</tr>
<tr>
<td>AVHRR</td>
<td>TMS/TIMS 1080e</td>
<td>Pixel-wise</td>
<td>27</td>
<td>0.35</td>
<td>38</td>
</tr>
</tbody>
</table>

The aggregated temperature was obtained by solving Eq. (26):

\[
\hat{T} = \left( \frac{\epsilon_v T_v^4 + \epsilon_s T_s^4}{\epsilon_v Fr + \epsilon_s (1 - Fr)} \right)^{1/4}
\]  

(27)
Fig. 4. A comparison of the aggregation schemes on the fractional vegetation and radiometric temperature fields for the field containing the ER05 eddy covariance station. The histogram consists of the 12 m airborne data, while the vertical lines indicate the 12 m pixel corresponding to the station, as well as aggregated values up to 780 m pixels, 1080 m, and AVHRR.

The affect of the aggregation schemes on the derived fluxes is examined next. A histogram is presented in Fig. 5 for 12 m pixels of the field in which the eddy covariance station was located. Vertical lines represent the measured value at the station (12 m pixel), the pixel-wise comparison (Pixel), the result of using the algorithm of Schuepp et al. (1990), the average value of the 12 m estimates (Avg), and the result of the flux calculated at the resolution of the AVHRR sensor (AVHRR). In the case of the latent heat flux, the histogram and the average of the 12 m pixels agree well with the measured flux. All of the other estimates underestimate the flux by approximately 100 W m$^{-2}$.

For the sensible heat flux, all estimates underestimate the measured flux with the pixel-wise comparison being the closest.

Note that the aggregated values of radiometric temperatures being higher than the average value of the 12 m field data, carries over to the aggregated estimates of the sensible heat flux being higher than the field average as well. This does not, however, explain the underestimation by the latent heat flux.

7.7. Interaction of surface heterogeneity and ABL height

As discussed previously, much of the work in understanding the effects of surface variability has focused on the feedbacks between the surface heterogeneity...
and interactions with the ABL. This is often approached by considering the height of the ABL. Many of the studies cited previously (e.g. Raupach and Finnigan, 1995; Mahrt, 2000) have developed order of magnitude estimates for whether or not the surface variability makes the application of the “mosaic” approach unrealistic.

In an attempt to ascertain the interaction between the ABL height and the surface variability within the SGP97 region the ABL height was modeled with the SVAT model. The development of the ABL height is modeled based on the formulation developed by Tennekes (1973) and extended by Zilitinkevich (1975).

This formulation models the change of the ABL height as a function of the downward heat flux from the capping inversion layer \( \theta_w \) and the strength of the inversion \( \Delta (K) \):

\[
\frac{dh}{dt} = -\frac{\theta_w}{\Delta}
\]

where the downward heat flux is a function of the surface heat flux \( \theta_w \):

\[
\theta_w = \frac{-c_1 \theta_w^0}{1 + c_2 \theta_w^0 |1/(g/\theta_w^{1/3})|^{1/3}}
\]

where \( g/\theta_w \) is the buoyancy parameter (m s\(^{-2}\) K\(^{-1}\)), \( c_1 \) and \( c_2 \) are dimensionless constants, and the strength of the inversion is modeled via McNaughton and Spriggs (1986):

\[
\frac{d\Delta}{dt} = \gamma \frac{dh}{dt} \frac{H}{\rho c_p h}
\]
where $\gamma_v$ is the gradient for virtual potential temperature at a height immediately above the ABL.

This was initialized with the radiosonde profile from the morning, and allowed to evolve with the day. The SVAT model was then inverted, in a manner similar to Eq. (22), to estimate the spatial variability in the ABL as a function of the remotely sensed data. The dominant length scale (as determined via the wavelet spectra) in the area is on the order of 800 m (Brunsell and Gillies, 2003). Therefore, the vegetation and temperature fields from the airborne data were aggregated to 780 m to which the model inversion algorithm was applied.

The modeled ABL heights range from approximately 1 to 1.5 km. Calculations based on Eq. (14) show that the region is under a microscale heterogeneity at least at the time these measurements were calculated, $L_{\text{hetero}}$ was 800 m (the dominant length scale of the surface variability, discussed in Brunsell and Gillies (2003)) and is significantly smaller than $C_{\text{blend}}u^2/u_*$. There are no measurements of the actual height of the ABL at the time that the remotely sensed data were collected. However, for the purpose of general understanding this exercise is still fruitful, as well as serving as further justification for the use of the SVAT modeling scheme in the SGP97 region.

8. Discussion

This paper examines issues involved with the coupling of remotely sensed data to a SVAT model in order to determine pixel scale energy fluxes. Following a review of the relevant processes, a discussion of various aggregation schemes ensued. An example case was conducted using data from the SGP97 dataset. The SVAT model shows good agreement between the fluxes derived from the high resolution airborne data and the surface eddy covariance towers. The satellite data had relatively poor agreement directly with surface measurements. However, when the high resolution flux estimates are aggregated using a decomposition of the vegetation and soil temperatures, the resultant fluxes agreed well with those calculated from the AVHRR sensor.

The comparison between surface measurements and remotely sensed estimates highlights one of the primary problems with the large scale application of satellite data for calculating surface energy fluxes, i.e. how to validate the resultant fluxes. Here, it is suggested that the direct comparison of satellite estimates with surface measurements is unrealistic due to differences in the spatial heterogeneity captured within the two different measurements. Pixel-wise comparison of the 12 m estimates of the fluxes result in small errors when compared to the eddy covariance data (approximately 15% for both sensible and latent heat). One interesting result concerned the use of estimates for the contribution to the turbulent flux as a function of the upwind distance (Schuepp et al., 1990). When this estimate was combined with the high resolution remotely sensed data, the errors were higher (although possibly acceptable) (about 27% for LE and 32% for $H$) as opposed to using the simple pixel-wise comparison. This is interesting since this a more physically realistic method for comparison of the flux with the tower data, and the various fields are not that variable in the upwind direction from the towers. When the high resolution flux estimates are aggregated using the physically meaningful temperature aggregation scheme, the comparison with AVHRR estimates are also acceptable (approximately 10% of LE and 35% for $H$).

The possible cause for the agreement between the high resolution data and the surface is the length scale of the surface variability. In the case of the SGP97 site, the average field size was on the order of 800 m, with the high resolution data having pixel sizes much smaller than that. Thus, the dominant scale of variability is easily captured by the high resolution data. However, this scale is completely missed by the AVHRR sensor. This issue is addressed more completely in Brunsell and Gillies (2003).

Other issues that were investigated here included the variation in remotely sensed input variables as a function of the level of aggregation. Specifically, the effects of using a physically based aggregation scheme on radiometric temperature as well as aggregating the fractional vegetation fields were examined. All estimates of the aggregated and satellite radiometric temperature data were higher than the average of the mean radiometric temperature calculated by linearly averaging the 12 m high resolution data. The aggregation scheme is supported by the close agreement between the AVHRR measurements and the aggregated high resolution data. The Fr field showed much less
variability with the majority of the estimates and the aggregated values being around the mean of the high resolution data. It is surmised that errors due to the calculation of the Fr field will be less significant than errors in the temperature field.

The effect of this variability on the resultant estimations of turbulent fluxes was examined next. The higher than average temperature aggregations resulted in higher than average sensible heat fluxes when compared to the average of the 12 m data calculated from the high resolution data. This translated into lower than average estimations of the latent heat flux.

The majority of methods for quantifying the level of heterogeneity used by the micrometeorological community are order of magnitude arguments relating the length scales of horizontal variability to ABL characteristics such as the height of the ABL and the intensity of turbulence ($u^*$). This issue was examined by looking at SVAT modeled values of the ABL height as a function of the surface vegetation and radiometric temperature. The results indicate that the “mosaic” approach to estimating fluxes is valid based on the 800 m length scale of the surface and ABL heights ranging from 1 to 1.5 km (i.e. microscale variability was present within the region). Note, however, that without actual measurements of the ABL height, little can be said in any conclusive manner. This is compounded by the fact that the SVAT model inherently assumes that the “mosaic” approach is valid. This matter should be examined in future field campaigns with measurements of the ABL characteristics.

The SGP97 field areas consisted primarily of agricultural fields. This allowed relatively straightforward modeling of the surface energy balance in this region; in that there were not large amounts of variability within the remotely sensed data. Future work should focus on field campaigns in areas with more surface variability so that the interaction between various land-cover types and the atmospheric fluxes can be examined.

Acknowledgements

The authors wish to thank Andy French and Tom Schmugge of the USDA-ARS, for assistance with the TMS/TIMS data. We would also like to thank John Praeger of NSTL, Ames and Bill Kustas of USDA-ARS for discussions concerning the eddy covariance data they collected during the SGP97 campaign. Funding was provided through a grant from NASA Cooperative Agreement No. NCC8-162 in support of the Global Energy and Water Cycle Experiment (GEWEX) Continental Scale International Project (GCIP) and Utah Agricultural Experiment Station, Utah State University, Logan, UT 83322-4810.

References


