Evaluating the Effects of Subpixel Heterogeneity on Pixel Average Fluxes

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Radiometric temperature observations $T_R(\varphi)$ at a sensor view angle $\varphi$ are routinely available from weather satellites such as the Geostationary Orbiting Environmental Satellite (GOES) and provide a unique spatially distributed boundary condition for surface energy balance modeling at regional scales. Reliable flux estimates over heterogeneous surfaces have been obtained using two-source models that implicitly account for differences between $T_R(\varphi)$ and aerodynamic temperature, $T_A$, by considering separately the contributions of soil/substrate and vegetation to $T_R(\varphi)$ observations and to the turbulent fluxes. A simple two-source energy balance model developed to use $T_R(\varphi)$ observations has been applied successfully to a wide range of vegetation cover conditions at the field scale. However, its application with course resolution weather satellite data (i.e., pixel resolution $\geq 1$ km) will invariably result in errors in pixel-averaged heat flux estimation for surfaces with significant variability in vegetation cover and stress conditions. Indeed, with the highest resolution of satellite $T_R(\varphi)$ data $\approx 100$ m, subpixel heterogeneity will still be significant for many landscapes, especially arid and semiarid areas. Uncertainty in flux estimation due to significant subpixel heterogeneity is examined using the simplified two-source model with $T_R(\varphi)$ inputs from simulations using a detailed plant-environment model (Cupid) under six different “homogeneous” surface conditions commonly found in semiarid and arid regions and under high and low winds. These surface types are comprised of shrub and tall riparian vegetation, high and low canopy cover, wet and dry surface soil moisture state, and stressed versus unstressed vegetation condition. From six homogeneous surface conditions defined by vegetation type, cover, surface moisture and stress, four mixed-pixel cases were constructed, each containing two contrasting surface types. Significant or unacceptable errors (i.e., $\approx 50$ W m$^{-2}$) in pixel-average heat fluxes are found in all four mixed-pixel cases, but the significant errors primarily occur when the fraction of the extreme surface condition (e.g., riparian wetland) comprises between $\approx 20\%$ and $80\%$ of the mixed-pixel. Additionally, the results are influenced by the wind conditions with a higher wind speed tending to reduce errors. This preliminary analysis suggests that when there is a significant discontinuity in surface conditions, particularly under low winds, the subpixel variability in energy fluxes will likely cause unacceptable errors in two-source model predictions. However, daytime wind speeds are typically $>2$ m s$^{-1}$ and the resolution of $T_R(\varphi)$ observations from weather satellites are relatively coarse (i.e., $\approx 5$–10 km), which means riparian areas are likely to comprise less than 10% of a pixel. Both of these factors are likely to reduce errors in heat flux predictions at these large spatial scales caused by using pixel-average inputs. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) instrument proposed for NASA’s Earth Observing System (EOS) has 90 m resolution. This will be useful for evaluating the impact of subpixel variability on flux predictions with coarser resolution data more routinely available from weather satellites.

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INTRODUCTION

Indirect estimates of surface fluxes over extensive areas based on remote sensing from satellites typically involve treating heterogeneous pixels in the same way as the homogeneous areas used to develop the original algorithms. Uncertainties associated with heterogeneous pixels are difficult to evaluate, because no in situ methods exist to measure surface fluxes reliably over such relatively large areas.
heterogeneous areas. Mixed pixels can present potential problems in remote sensing of surface fluxes; unfortunately, model output fluxes from pixel-averaged inputs (satellite-based sensors inherently provide average values for each pixel) in heterogeneous areas do not always provide the same pixel-level fluxes as averaging model-output fluxes from runs on homogeneous subpixel areas. Therefore, we attempt to evaluate the consequences of such pixels composed of mixed vegetation and soil conditions using model simulations.

The methodology we use is to run validated models using homogeneous inputs and calculate homogeneous output fluxes. Then we average the model-input quantities (e.g., surface temperature and vegetative cover) from various homogeneous subpixel areas that make up a heterogeneous pixel, and use these averaged inputs in the model to calculate a composite flux for the mixed pixel. In general, the area-weighted homogeneous model fluxes are not equal to the composite fluxes calculated from area-weighted inputs to the model. Our objective is to determine the conditions when errors associated with remote sensing of mixed pixels cause significant errors in surface-flux estimation.

A recent review of dual-source models by Zhan et al. (1996) suggests that the model proposed by Norman et al. (1995) (hereafter referred to as the N95 model) can yield satisfactory estimates of sensible, H, and latent heat flux, LE, over different surfaces and is relatively insensitive to the expected errors associated with estimating many of its input parameters and variables. More recently Kustas et al. (1999) evaluated how well the model realistically simulates the separate flux contributions from the soil surface and vegetation using a comprehensive plant-environment (PE) model Cupid (Norman and Campbell, 1983; Norman and Arkebauer, 1991). Cupid simulates radiation exchange, turbulent fluxes and \( T_{\nu}(\phi) \) for plant canopies by accommodating all the generality inherent in a comprehensive PE model with parametrizations of important processes at the leaf level (cm) and integrating mechanistic equations to the canopy level (10–100 m). Cupid was applied to field data collected from a semiarid rangeland containing partial vegetation cover randomly distributed over the landscape. The simulated \( T_{\nu}(\phi) \) values computed from Cupid were used as input to the simple two-source model for computing the energy balance of the soil and vegetation. These flux estimates compared satisfactorily with Cupid output.

Several modifications to the simplified two-source model have been made based on comparisons with Cupid, but primarily from observations from a sparse cotton row crop (Kustas and Norman, 1999a,b). These changes include: 1) replacing the commonly used Beer’s law expression for estimating the divergence of net radiation through the canopy layer with a more physically based algorithm; 2) implementing a simple method to address the effects of clumped vegetation on radiation divergence and wind speed inside the canopy layer; 3) adjusting the magnitude of the Priestley–Taylor (Priestley and Taylor, 1972) coefficient used in estimating canopy transpiration; and 4) modifying the soil resistance algorithm for estimating soil sensible heat flux transfer.

For regional scale applications using satellite data, the simplified two-source model parametrizations have been adopted in an operational land surface–atmosphere model ALEXI (Anderson et al., 1997; Mecikalski, 1999) because its input requirements can be obtained from operational weather data and satellite (i.e., GOES) information. In the application of satellite data for large area mapping of fluxes, the effect of heterogeneity of surface conditions at the subpixel scale and its impact on the fluxes is not well known. Methods for dealing with heterogeneity effects are being addressed in the hydrologic and atmospheric modeling communities. Giorgi and Avissar (1997) provide a detailed review of methodologies for dealing with subgrid scale heterogeneity. Interestingly, observational studies on the effects of surface heterogeneity on surface-flux aggregation using remote sensing with surface energy balance models suggest that application of simple averaging rules to define model inputs cause relatively minor errors (Sellars et al., 1995; Kustas and Humes, 1996; Friedl, 1997). These results were probably obtained under conditions where the variability of surface characteristics was not large enough to cause significant errors.

The set of conditions simulated by Cupid provide more extreme cases than have existed naturally in interdisciplinary field campaigns involving remote sensing. Radiometric temperatures simulated by Cupid will represent several different homogeneous surface types defined by surface wetness, vegetation cover, stress, and roughness. Four mixed pixel cases, each containing two contrasting homogeneous surface types and corresponding radiometric temperatures simulated from Cupid, will be used for evaluating the effect of subpixel heterogeneity on pixel-averaged fluxes. Pixel-averaged fluxes will be computed with the simplified two-source model using pixel-averaged inputs derived by weighting the fractional area of the mixed pixel comprised of the two contrasting surface types. These values will be compared to a weighted average of the fluxes from the two homogeneous surface types comprising the mixed pixel. The four mixed pixel cases represent both an extreme condition with a riparian wetland containing either shrub or tall vegetation under high cover adjacent to stressed shrub uplands and more typical cases of an ephemeral stream bed supporting either shrub or tall vegetation under high cover adjacent to shrub uplands under uniformly dry surface moisture conditions. This preliminary analysis provides both an upper bound of the potential errors and what might be the typical errors caused by subpixel heterogeneity in arid and semiarid environments.
Figure 1. N95 model flux predictions versus Cupid output for meteorological and vegetation cover, stress and surface soil moisture conditions described in the text. The line represents perfect agreement with Cupid output.

MODEL OVERVIEW

A detailed description of the original N95 model can be found in Norman et al. (1995). Other versions of the model adapted to use multiple-view angle $T_b\phi$ observations is described in Kustas and Norman (1997). Changes to several of the original N95 formulations to account for temporal variations in net radiation divergence through the canopy layer and in the soil heat flux-soil net radiation ratio are described in Kustas et al. (1998). The most recent modifications to the formulations are described by Kustas and Norman (1999a,b) and Kustas et al. (1999) based on field data from a sparsely vegetated surface and Cupid simulations. An overview of the model structure and of the new parametrizations is given in the Appendix. Many of the modifications to the original N95 model have a dramatic impact on model predictions for sparse vegetative canopy covered surfaces.

Comparison of fluxes predicted by the Cupid and the N95 models for a range of surface conditions is illustrated in Figure 1 (Kustas et al., 1999). There were 22 cases simulated by Cupid involving the following conditions: two wind speeds (1 m s$^{-1}$ and 5 m s$^{-1}$), leaf area index LAI=0.5, 1.5, and 3.0, unstressed vegetation with a dry soil surface, unstressed vegetation with a wet soil surface, and stressed vegetation with a dry soil surface. In addition there was an unstressed tall riparian vegetation case with LAI=3.0 and canopy height, $h_c=5$ m. The weather data used (except for the wind speed) came from a clear dry day during the Monsoon 90 Experiment (Kustas and Goodrich, 1994). The comparison in Figure 1 is for 1030 local time, which is the approximate overpass time planned for EOS-AM1 platform containing the ASTER instrument (Yamaguchi et al., 1998). At this time solar radiation, $R_s$, was 880 W m$^{-2}$, the relative humidity $rh$ was 33%, and the air temperature $T_a$ was approximately 28.5°C. The $T_b\phi$ values simulated from Cupid were used as input by the N95 model (see Table 1). The $r^2$ values for sensible heat flux $H$ and latent heat flux $LE$ in Figure 1 are 0.85 and 0.90, respectively, indicating that the two-source model is accounting for a significant amount of the variation in the heat fluxes simulated by Cupid. However, discrepancies in $H$ and $LE$ in some cases reach ~100 W m$^{-2}$ (see Table 1), indicating that there are conditions where differences in flux predictions
between the two models are significant (see Kustas et al., 1999). Mean absolute differences (MAD) between Cupid and N95 flux predictions for $R_s$, $G$, $H$, and $LE$ are on the order of 5 W m$^{-2}$, 45 W m$^{-2}$, 50 W m$^{-2}$, and 40 W m$^{-2}$, respectively.

These differences are slightly greater than flux comparisons made using field data from the Monsoon ’90 experiment under daytime conditions, where MAD values between N95 model derived and observed $R_s$, $G$, $H$, and $LE$ were on the order of 20 W m$^{-2}$, 20 W m$^{-2}$, 30 W m$^{-2}$, and 45 W m$^{-2}$, respectively. With the same field data, Cupid predictions versus observations yielded MAD values for $R_s$, $G$, $H$, and $LE$ on the order of 15 W m$^{-2}$, 25 W m$^{-2}$, 30 W m$^{-2}$, and 40 W m$^{-2}$, respectively (Kustas et al., 1999). The results with the observations indicate that the performance of the two models in predicting surface energy fluxes is similar under these field conditions. In most cases, the discrepancies between heat flux predictions of the two models (Cupid and N95) using simulated data are comparable to the differences between either of the models and the observations. The slightly larger discrepancies in heat flux predictions between the two models is mainly due to the much wider range in vegetation cover and stress conditions being simulated compared to field observations typically available in model validation studies (e.g., Zhan et al., 1996).

### METHODS

**Choice of Subpixel Surface Properties**

The pixel resolution of present and future satellite radiometers providing $T_h(\phi)$ images ranges from ~100 m (e.g., ASTER and Landsat TM) to ~4 km (GOES); therefore, pixels will contain a mixture of vegetation and soil. In many cases riparian areas are only tens of meters...
Figure 2. Examples of the four mixed pixel cases, which are composed of six surface types. Case 1a represents a riparian wetland with shrubs and stressed shrubs in dry uplands. Case 1b is a riparian wetland with tall plants and stressed shrubs in dry uplands. Case 2a is an ephemeral stream bed with shrubs and unstressed shrubs in dry uplands. Case 2b is an ephemeral stream bed with tall plants and unstressed shrubs. Each case is characterized by the fraction of the pixel area occupied by each surface type. For example, in mixed pixel Case 1a, $f_{SLD}$ is the fraction occupied by surface type $SLD$ and $f_{UHW} = 1 - f_{SLD}$ is the pixel fraction occupied by surface type $UHW$.

<table>
<thead>
<tr>
<th>Case 1a</th>
<th>Case 1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{SLD}$</td>
<td>$f_{THW}$</td>
</tr>
<tr>
<td>Stressed shrub, Low cover, Dry soil surface (SLD)</td>
<td>Stressed shrub, Low cover, Dry soil surface (SLD)</td>
</tr>
<tr>
<td>Unstressed shrub, High cover, Wet soil surface (UHW)</td>
<td>Tall (unstressed) plants, High cover, Wet soil surface (THW)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Case 2a</th>
<th>Case 2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{UHD}$</td>
<td>$f_{ULD}$</td>
</tr>
<tr>
<td>Unstressed shrub, Low cover, Dry soil surface (ULD)</td>
<td>Unstressed shrub, Low cover, Dry soil surface (ULD)</td>
</tr>
<tr>
<td>Unstressed shrub, High cover, Dry soil surface (UHD)</td>
<td>Tall (unstressed) plants, High cover, Dry soil surface (THD)</td>
</tr>
</tbody>
</table>

Wide so that satellite $T_{b}(\phi)$ observations will commonly contain a mixture of riparian vegetation and the surrounding area, which for semiarid areas is typically sparsely vegetated. In the present set of conditions used for the Cupid simulations, the greatest contrasts in energy flux partitioning and in the magnitude of $T_{b}(\phi)$ comes from the simulations using stressed shrub vegetation (represented by the symbol S) under low cover, where $LAI=0.5$ (represented by the symbol L) and dry soil (represented by the symbol D) versus unstressed shrub vegetation (represented by the symbol U) with high cover where $LAI=3$ (represented by the symbol H) and wet surface soil moisture (represented by the symbol W) conditions; that is, $SLD$ versus $UHW$. Another extreme case is contrasting the stressed shrub under low cover and dry soil with tall unstressed riparian vegetation with $h_{c}=5$ m (represented by the symbol $T$) under high cover (i.e., $LAI=3$) and wet surface soil moisture; that is, $SLD$ versus $THW$. We also investigated more typical cases where the pixel is composed of either unstressed shrub with low cover and an ephemeral stream bed containing unstressed shrub or tall vegetation and high cover under dry surface soil moisture conditions.

The flux output from the two-source model using input values of the corresponding $T_{b}(\phi)$ simulated by Cupid are listed in Table 1 for the following set of conditions: 1 m s$^{-1}$ and 5 m s$^{-1}$ wind speeds, $R_{n}=850$ W m$^{-2}$, $rh=33\%$, and $T_{a}=28.5$°C. Also included for comparison purposes are the flux predictions from Cupid. MAD values between Cupid and two-source model predictions are on the order of 5 W m$^{-2}$ for $R_{n}$ and 50 W m$^{-2}$ for $G$, $H$, and $LE$.

The extreme to moderate contrasts in surface conditions were achieved by using six surface types in the Cupid simulations resulting in the heat fluxes and simulated values of $T_{b}(\phi)$ shown in Table 1 under the low and high wind speed conditions. The six surface types are represented by the following three symbol sequences which are used throughout the paper and as subscripts in equations describing averaging schemes:
Table 2. Two-Source Model Parameters Defined for the Three Vegetation Cover/Soil Moisture Conditions Simulated by Cupid

<table>
<thead>
<tr>
<th>Vegetation Cover and Soil Moisture Condition</th>
<th>LAI*</th>
<th>(f_c)</th>
<th>(h_c) (m)</th>
<th>(\Omega)</th>
<th>(l_p) (m)</th>
<th>(f_p)</th>
<th>(\alpha_p)</th>
<th>(z_{om}) (m)</th>
<th>(d_{om}) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stressed shrub, Low cover, Dry soil (SLD)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.7</td>
<td>0.01</td>
<td>0.8</td>
<td>0.2</td>
<td>0.07</td>
<td>0.24</td>
</tr>
<tr>
<td>Unstressed shrub, High cover, Wet soil (UHW)</td>
<td>3</td>
<td>0.8</td>
<td>0.5</td>
<td>0.1</td>
<td>0.01</td>
<td>1.3</td>
<td>0.03</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>Tall unstressed plants, High cover, Wet soil (THW)</td>
<td>3</td>
<td>0.8</td>
<td>0.5</td>
<td>0.1</td>
<td>1.3</td>
<td>0.34</td>
<td>3.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unstressed shrub, Low cover, Dry soil (ULD)</td>
<td>0.5</td>
<td>0.3</td>
<td>0.5</td>
<td>0.7</td>
<td>0.01</td>
<td>1.3</td>
<td>0.07</td>
<td>0.24</td>
<td></td>
</tr>
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<td>Unstressed shrub, High cover, Dry soil (SLD)</td>
<td>3</td>
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<td>0.1</td>
<td>0.01</td>
<td>1.3</td>
<td>0.03</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>Tall unstressed plants, High cover, Dry soil (THD)</td>
<td>3</td>
<td>0.8</td>
<td>0.5</td>
<td>0.1</td>
<td>0.05</td>
<td>1.3</td>
<td>0.34</td>
<td>3.95</td>
<td></td>
</tr>
</tbody>
</table>

* LAI: leaf area index.
* \(f_c\): fractional vegetation cover related to LAI via Eq. (3), but includes clumping factor correction for LAI=0.5 (see Kustas and Norman, 1999a).
* \(h_c\): canopy height with estimates based on field observations from a semiarid rangeland (Kustas and Goodrich, 1994).
* \(\Omega\): clumping factor used to account for the fact that vegetation is typically clumped under sparse canopy cover conditions, thus increasing wind and radiation penetration compared to the same LAI randomly distributed over the surface (Kustas and Norman, 1999a,b). See also Campbell and Norman (1998).
* \(l_p\): effective leaf width dimension used in calculating canopy boundary layer resistance (Norman et al., 1995.)
/ \(f_p\): fraction of vegetation assumed "green" or transpiring (see Norman et al., 1995).
* \(\alpha_p\): Priestley–Taylor coefficient (Priestley and Taylor, 1972) used in estimating canopy transpiration in the two-source model (see Norman et al., 1995). Recently modified to be adjustable for stress and advective conditions (see Kustas et al., 1999; Kustas and Norman, 1999a). Average value is listed for the two wind speed cases.
* \(z_{om}\) and \(d_{om}\): momentum roughness length and displacement height estimated from the simplified equations of Raupach (1994) using \(h_c\).

SDS = Stressed shrub under Low cover and Dry surface soil moisture,
UHW = Unstressed shrub under High cover and Wet surface soil moisture,
THW = Tall (unstressed) plants under High cover and Wet surface soil moisture,
ULD = Unstressed shrub under Low cover and Dry surface soil moisture,
UHD = Unstressed shrub under High cover and Dry surface soil moisture,
THD = Tall (unstressed) plants under High cover and Dry surface soil moisture.

To simulate the influence of mixed surface types within pixels, we considered two main environmental conditions: 1) stressed upland shrubs under low cover having minimal evaporation (surface type SLD) adjacent to a riparian wetland area with high cover undergoing maximal evapotranspiration (surface types UHW and THW) and 2) dry surface moistures conditions having un-stressed upland shrubs with low cover (surface type ULD) adjacent to an ephemeral stream bed with unstressed vegetation under high cover with a dry soil surface (surface types UHD and THD). From these two conditions we have created four mixed pixel cases by considering two different plant heights in the riparian area and ephemeral stream bed using a) \(h_c=0.5\) m for shrubs and b) \(h_c=5\) m for tall vegetation. Therefore, the four mixed pixel cases consist of the following surface types: 1a) SLD and UHW; 1b) SLD and THW; 2a) ULD and UHD; 2b) ULD and THD. These four mixed pixel cases are summarized in Figure 2. Cases 1a and 1b are meant to illustrate extremes in evapotranspiration and surface temperature while cases 2a and 2b illustrate the effect of vegetation cover and roughness under uniformly dry surface soil moisture conditions. All four cases typify mixed pixels in semiarid regions. To further evaluate the effect of surface variability on mixed pixel derived fluxes, the influence of wind speed was considered by evaluating the fluxes under low (1 m s\(^{-1}\)) and high (5 m s\(^{-1}\)) wind speeds.

Subpixel heterogeneity from mixtures of riparian shrubs and trees and stressed shrubs will cause an error in the calculated flux because the relationship between \(T_{R}(g)\) and the heat fluxes is nonlinear. Using the MAD values between the two-source and Cupid flux predictions as a guide, we define significant errors in pixel-average heat fluxes when differences from the “true” average (see below) are greater than 50 W m\(^{-2}\). A threshold of 50 W m\(^{-2}\) is also in agreement with typical average differences found between model and measured heat fluxes and is the typical uncertainty in turbulent heat flux measurement systems under daytime conditions (e.g., Norman et al., 1995; Friedl, 1996; Kustas and Norman, 1997).

**Deriving Pixel Average Model Input Parameters**

The composite fractional cover for each of the four \((i=1a, 1b, 2a, 2b)\) mixed pixel cases (Fig. 2) was computed by simply weighting the cover fraction value for each surface type \((f_{c,j})\) where \(j=SLD, UHW, THW, ULD, UHD,\) and \(THD\) by the corresponding fractional area that this surface type occupies \((f_j)\). For example, for mixed pixel case 1a comprised of surface types UHW and SLD, the composite fractional cover \(f_{c,1a}\) would be computed as

\[
\overline{f_{c,1a}} = f_{c,1a}f_{c,UHW} + f_{c,1a}f_{c,SLD}.
\]  

Then the composite LAI for mixed pixel case \(i, \overline{LAI}_i\), is computed via an exponential relationship [Eq. (2)] between fractional cover and leaf area index (Choudhury, 1987):

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The composite value for the canopy height $\bar{h}_{CL}$ and each of the vegetation parameters in Table 2 for the mixed pixel were estimated using the weighting scheme described by Eq. (1).

The roughness length $z_{O,M}$ and displacement height, $\delta_{O,i}$ for the mixed pixels were computed from the equations of Raupach (1994) using the composite values of $\bar{L}_{AI,i}$ and $\bar{h}_{CL,i}$ values.

The composite value of $T_{R,i}(\phi), \bar{T}_{R,i}$ for each one of the four mixed pixel cases with contrasting surfaces illustrated in Figure 2 was estimated as follows:

\[
\bar{T}_{R,i} = \sum_{j} f_{j} T_{R,j} + \bar{f}_{H} T_{R,H}, \quad (3a)
\]

\[
\bar{T}_{E,i} = \sum_{j} f_{j} T_{E,j} + \bar{f}_{H} T_{E,H}, \quad (3b)
\]

\[
\bar{T}_{L,i} = \sum_{j} f_{j} T_{L,j} + \bar{f}_{H} T_{L,H}, \quad (3c)
\]

\[
\bar{T}_{R,i} = \sum_{j} f_{j} T_{R,j} + \bar{f}_{H} T_{R,H}, \quad (3d)
\]

\[
\bar{f}_{j} = 1 - \exp(-\beta \bar{L}_{AI}), \quad (2)
\]

where $\beta$ is a function of the leaf angle distribution (e.g., $\beta=0.5$ for randomly distributed leaves).

The predicted composite fluxes (denoted by flux symbols enclosed in $\langle \rangle$, i.e., $\langle H \rangle$), using $\bar{T}_{R,i}$ as inputs are compared to the "true" flux averages. These "true" flux averages are computed using the same linear weighting scheme given by Eq. (1) applied to output fluxes predicted for homogeneous surface type $j$ (see Table 1). From scalar conservation requirements Raupach (1995) shows formally that the area averaged scalar fluxes, $H$ and $LE$, require elemental flux densities (i.e., fluxes from each surface type) to be weighted by the fraction of area occupied and summed across the landscape. Assuming horizontal fluxes between surface types are small compared to vertical fluxes then by energy conservation $R_{N}$ and $G$ also average linearly. For the four contrasting surface conditions the true average $H$ is simply computed by the following expressions:

\[
\bar{H}_{u} = \sum_{j} f_{j} H_{u,j} + \bar{f}_{H} H_{u,H}, \quad (4a)
\]

\[
\bar{H}_{l} = \sum_{j} f_{j} H_{l,j} + \bar{f}_{H} H_{l,H}, \quad (4b)
\]

\[
\bar{H}_{a} = \sum_{j} f_{j} H_{a,j} + \bar{f}_{H} H_{a,H}, \quad (4c)
\]

\[
\bar{H}_{w} = \sum_{j} f_{j} H_{w,j} + \bar{f}_{H} H_{w,H}, \quad (4d)
\]

Thus differences between the composite sensible heat flux ($H$) and the true average $\bar{H}$, indicate the potential errors in using model input parameters averaged over mixed pixels. These same equations are used for estimating the true average value of the other energy balance components by replacing $H$ with $R_{N}$, $G$, and $LE$.

In this model comparison study, we are assuming no interaction between the adjacent surface types. In addition, riparian areas typically have horizontal scales of a few hundred meters; hence, meteorological quantities were treated as horizontally uniform (Raupach and Finnigan, 1995). For riparian wetland areas in desert environments (i.e., mixed pixel case 1a or 1b) assuming no interaction between adjacent surface types and use of Eqs. (4a), (4b), (4c), and (4d) may not always be appropriate (Hipp et al., 1998). However, model simulations suggest that this assumption is reasonable for a fairly wide range of conditions (Raupach and Finnigan, 1995).

### RESULTS AND DISCUSSION

MAD values between the composite and true average fluxes using the N95 model are computed for each mixed pixel case over the whole range in fractional cover amount occupied by the surface types illustrated in Figure 2. Additionally, as a means of assessing the uncertainty in N95
Figure 3. Values of composite fluxes from the N95 model (■) and true flux averages from the N95 (○) and Cupid (▲) models for the following mixed pixel cases: Case 1a (i.e., surface types SLD and UHW) and Case 1b (i.e., surface types SLD and THW) under low wind speed (\(u=1 \text{ m s}^{-1}\)). See text and Table 3 for canopy cover, stress, and soil moisture definitions.
flux predictions, MAD values between the two-source and Cupid-derived true average fluxes using Eq. (4) were computed.

MAD values for the mixed pixel cases 1a and 1b, which contain contrasting surface SLD and UHW, and SLD and THW, are listed in Table 3. For the light wind case where \( u = \text{1 m s}^{-1} \), significant differences occur between composite and true average heat fluxes, especially between \( \langle LE \rangle \) and \( \overline{LE} \), where differences are typically >100 W m\(^{-2} \) (Fig. 3). The dependence of flux estimates for the light wind case as a fraction of the pixel occupied by surface type SLD is shown graphically in Figure 3. Differences between \( \langle H \rangle \) and \( \overline{H} \), and \( \langle LE \rangle \) and \( \overline{LE} \), are extreme for mixed pixel case 1b when \( f_{\text{SLD}} \geq 0.2 \) and \( f_{\text{ULD}} \leq 0.8 \). Note that differences between composite and the true average fluxes are generally smaller at the endpoints; in fact, the differences should equal zero at \( f_{\text{SLD}} = 0 \) and 1 when comparing composite and true average fluxes predicted by the N95 model. The true average flux values from Cupid and the N95 model are not significantly different, with MAD values less than 50 W m\(^{-2} \) for \( G \) and \( \overline{H} \), and less than 10 W m\(^{-2} \) for \( R_{\text{s}} \) and \( \overline{LE} \) (see Table 3). Compared to the low wind case, for the high wind case where \( u = \text{5 m s}^{-1} \) MAD values between the composite and true average heat fluxes are higher for case 1a (i.e., surface types SLD and UHW) and lower for case 1b (i.e., surface types SLD and THW). The MAD values between Cupid and the N95 model true average flux predictions using \( u = \text{5 m s}^{-1} \) are similar to the low wind speed condition for case 1a, except for \( \overline{LE} \). The higher wind speed condition tends to cause differences between the composite and true average fluxes to be of opposite sign for \( G \), \( H \), and \( LE \) compared to the low wind condition (Fig. 4). Similar to the low wind speed condition, the differences between composite and true average fluxes are generally smaller at the endpoints. In general, the largest differences in the heat fluxes, especially between \( \langle LE \rangle \) and \( \overline{LE} \), tend to be when \( f_{\text{SLD}} \geq 0.2 \) and \( f_{\text{ULD}} \leq 0.8 \) (Figs. 3 and 4). This means that when the riparian wetland either occupies greater than 80% or less than 20% of the mixed pixel, errors between \( \langle LE \rangle \) and \( \overline{LE} \) are relatively small.

MAD values for the mixed pixel cases 2a (i.e., surface types ULD and UHD) and 2b (i.e., surface types ULD and THD) are listed in Table 4 (cf. Fig. 5). For the low wind case, discrepancies between composite and true average fluxes are similar to the results in Table 3. On the other hand, there are significantly larger differences for case 2b between \( H_{\text{b}} \) and \( \overline{LE}_{\text{b}} \) predicted by Cupid versus the N95 model (cf. Table 3). This suggests that the differences between composite and true average fluxes for case 2b are due in part to two-source model uncertainty in predicting the fluxes for the THD case in particular (see Table 1). For case 2b, differences in heat fluxes between composite and the true average change sign as the fraction of the pixel occupied by surface type ULD, \( f_{\text{ULD}} \), increases from 0.3 but again changes sign for \( f_{\text{ULD}} \geq 0.6 \). This behavior differs from the mixed pixel case 1b (i.e., surface types SLD and THW) under the low wind speed condition (Fig. 3). Using the high wind speed condition, the MAD values between composite and true average fluxes listed in Table 4 are significantly smaller for both contrasting surface conditions. Moreover, differences between Cupid and two-source model predictions of the true average fluxes are significantly less than 50 W m\(^{-2} \). As shown in Figure 6 for the high wind speed condition, much smaller differences or errors are computed over the whole range in \( f_{\text{ULD}} \), especially in the heat fluxes. As in the previous two cases (1a and 1b), again it appears that for cases 2a and 2b, when the ephemeral streambed either occupies greater than 80% or less than 20% of the mixed pixel, errors between \( \langle LE \rangle \) and \( \overline{LE} \) tend to be relatively small.

**CONCLUSIONS**

These results suggest that subpixel variability can cause a significant departure of the composite fluxes (primarily the turbulent fluxes \( H \) and \( LE \)) estimated with \( T_{E} \) compared to the “true” average values, \( \overline{H} \) and \( \overline{LE} \), computed by Eqs. (4). These discrepancies are influenced not only by the level of variability in vegetation cover and stress condition, but also by the wind speed. Therefore, it may be very difficult to define conditions priori under which the subpixel heterogeneity will not cause significant errors in heat flux calculations using \( T_{E} \).

It does appear, however, that for higher wind speed conditions, namely, \( u \sim 5 \text{ m s}^{-1} \), errors in flux predictions caused by relatively extreme subpixel variability in vegetation conditions tend to be smaller, although in many cases still are significant. Clearly, if a pixel contains marked changes or discontinuities in vegetation type, fractional cover, and stress/soil moisture conditions, using this composite scene with simple averaging rules for model inputs is likely to cause substantial errors. The mixed pixel cases that have the greatest potential for causing significant errors in heat flux predictions (i.e., \( \langle H \rangle \)−\( \overline{H} \), and \( \langle LE \rangle \)−\( \overline{LE} \)\( \geq 50 \) W m\(^{-2} \)) using composite input parameters in the N95 model are cases 1a (i.e., surface types SLD and UHW), 1b (i.e., surface types SLD and THW), and 2b (i.e., surface types ULD and THD) under low wind speeds. For the high wind speed condition, only mixed pixel case 1a appears to have significant discrepancies between composite and true average heat fluxes.

The errors are, in some cases, of the same order of magnitude as differences between Cupid and N95 model estimates of the true average fluxes (i.e., mixed pixel case 2b under low wind speed condition). However, wind speed observations in semiarid areas are normally greater than 1 m s\(^{-1} \) during daytime convective conditions. For example, with the Monsoon ’90 data set, daytime wind
Figure 4. Values of composite fluxes from the N95 model (■) and true flux averages from the N95 (○) and Cupid (▲) models for the following mixed pixel cases: Case 1a (i.e., surface types SLD and UHW and Case 1b (i.e., surface types SLD and THW) under high wind speed (u=5 m s⁻¹). See text and Table 3 for canopy cover, stress, and soil moisture definitions.
speeds averaged ~3.5 m s\(^{-1}\) (Kustas et al., 1999). Therefore, low wind conditions during daytime periods are likely to be the exception rather than the norm.

In almost all cases, the extreme surface condition (e.g., riparian wetland) has to occupy at least 20% of the scene before excessive errors >100 W m\(^{-2}\) are observed. In many arid and semiarid regions, it is conceivable a sensor with 1 km resolution will have up to 50% of a pixel comprised of a riparian area resembling surface type UHW or THW. For these mixed pixel cases, large errors in heat flux predictions are likely using pixel-average inputs. However, at 5–10 km pixel resolution, the riparian zone is likely to occupy less than 10% of the mixed pixel. The results of this study indicate relatively small errors are expected in mixed pixel cases having less than 20% of an extreme surface condition, such as a riparian wetland. Thus application of the two-source model with such coarse pixel resolution data collected over arid and semiarid landscapes will likely result in relatively small errors in area-average heat flux predictions at these larger spatial scales using pixel-average inputs.

Experimental observations under the types of contrasting conditions simulated by Cupid as well as further model comparisons are needed to validate these results. With the ASTER instrument on NASA’s EOS-AM1 platform, 90-m-resolution \(T_R\) data will be available (Yamaguchi et al., 1998). Application of these data with the simplified two-source model will provide a unique scheme for evaluating the impact of subpixel variability on flux predictions using coarser resolution weather satellite data with regional scale models such as ALEXI.

APPENDIX: OVERVIEW OF N95 MODEL

A simple model for relating remotely-sensed surface radiometric temperatures to surface energy fluxes arises from treating the vegetative canopy as one layer and the soil as a second layer. With the use of a single emissivity to represent the combined soil and vegetation, the ensemble directional radiometric temperature \(T_R(\varphi)\) is related to the fraction of the radiometer view occupied by vegetation as follows:

\[
T_R(\varphi) = \left[ f(\varphi) T_C + (1-f(\varphi)) T_s \right]^{1/n}, \tag{A.1}
\]

where \(T_C\) and \(T_s\) are the thermodynamic temperatures of the vegetation canopy and soil surface, respectively, and are assumed to represent spatially weighted averages of the sunlit and shaded portions of the canopy and soil, respectively, and \(n \sim 4\) (Becker and Li, 1990). The fraction of the field of view of the infrared radiometer occupied by canopy, \(f(\varphi)\), depends upon the view zenith angle \(\varphi\) canopy type and fraction of vegetative cover \(f_c\). For many vegetated surfaces, assuming a random canopy with a spherical leaf angle distribution is reasonable so that \([\text{Eq. (A.2)}]\)

\[
f(\varphi) = 1 - \exp \left[ -0.5 \frac{\cos \varphi}{\cos \varphi} \right] = 1 - \exp \left[ \ln(1-f_c) \cos \varphi \right]. \tag{A.2}
\]

The use of \(T_R(\varphi)\) in a convective heat flux equation frequently involves the controversial assumption that \(T_R(\varphi)\) is equivalent to the so-called “aerodynamic temperature” \(T_o\) of the surface. \(T_o\) is the temperature that satisfies the bulk transport expression having the form \([\text{Eq. (A.3)}]\)

\[
H = \rho C_p \frac{(T_o - T_A)}{R_{H\text{a}}}, \tag{A.3}
\]

where \(H\) is the sensible heat flux (W m\(^{-2}\)), \(\rho C_p\) is the volumetric heat capacity of air (J m\(^{-3}\) K\(^{-1}\)), \(T_A\) is the air temperature (K) at some reference height above the surface, and \(R_{H\text{a}}\) is the resistance to heat transport (s m\(^{-1}\)), which is calculated from canopy height, sensible heat flux, and wind speed using the familiar log-profile equations (Brutsaert, 1982; Norman et al., 1995).

The net energy balance of the soil-canopy system includes net radiation (\(R_{\text{a}}\)), sensible heat flux (\(H\)), latent heat flux (\(LE\)) and soil heat or conduction flux (\(G\)) so
Figure 5. Values of composite fluxes from the N95 model (■) and true flux averages from the N95 (◇) and Cupid (▲) models for the following mixed pixel cases: Case 2a (i.e., surface types ULD and UHD and Case 2b (i.e., surface types ULD and THD) under low wind speed (u = 1 m s⁻¹). See text and Table 4 for canopy cover, stress, and soil moisture definitions.
Figure 6. Values of composite fluxes from the N95 model (■) and true flux averages from the N95 (♦) and Cupid (▲) models for the following mixed pixel cases: Case 2a (i.e., surface types ULD and UHD) and Case 2b (i.e., surface types ULD and THD) under high wind speed \((u=5 \text{ m s}^{-1})\). See text and Table 4 for canopy cover, stress and soil moisture definitions.
that (neglecting photosynthesis) [Eq. (A.4)]

\[ R_N = H + LE + G \]  \hspace{1cm} (A.4)

The equations for computing fluxes from the soil and canopy components, denoted by subscripts \( s \) and \( c \), respectively, are as shown in Eqs. (A.5) and (A.6):

\[ R_{N,s} = H_s + LE_s + G, \]  \hspace{1cm} (A.5)

\[ R_{N,c} = H_c + LE_c, \]  \hspace{1cm} (A.6)

with \( R_N = R_{N,s} + R_{N,c} \). The net radiation divergence of the canopy is estimated separately for visible, near-infrared, and thermal wavelengths. Radiation absorption and scattering in visible and near-infrared wavelengths can be estimated from the analytical solution of Goudriaan (1977), which is discussed in Campbell and Norman (1998). Since the reflection and absorption of radiation in the visible and near-infrared wavelengths is markedly different for vegetation and soils, the visible and near-infrared albedos of the soil and vegetation were evaluated separately before combining to give an overall shortwave albedo.

Thermal radiation absorption by the soil and canopy are given approximately by (Kustas and Norman, 1999a) as in Eqs. (A.7) and (A.8):

\[ L_{N,s} = \exp(-\kappa_L LAI) \left[L_{s,h} + \left[1 - \exp(-\kappa_L LAI)\right] \left[L_{c,h} - L_{s} \right]\right], \]  \hspace{1cm} (A.7)

\[ L_{N,c} = \left[1 - \exp(-\kappa_L LAI)\right] \left[L_{s,h} + L_{s} - 2L_{c}\right], \]  \hspace{1cm} (A.8)

where the extinction coefficient \( \kappa_L \) depends on leaf angle distribution and leaf area index (LAI) (Campbell and Norman, 1998) and \( L_{c,h} \), \( L_{s,h} \), and \( L_{s,h} \) are the long-wave emissions from the canopy, soil, and sky, respectively. \( L_c \) and \( L_s \) are computed from the Stefan–Boltzmann equation using canopy temperature and soil temperature, and \( L_{s,h} \) is computed from shelter-level air temperature and vapor pressure (Brutsaert, 1982). The total absorbed radiation by the canopy and soil is the sum of visible, near-infrared, and thermal portions. The radiative exchange algorithms used in the model apply to vegetative canopies with leaves randomly distributed over the surface. When the leaves are not randomly distributed over the surface but clumped as in the case of row crops, they may only intercept 60–80% of the radiation in comparison to the same crop randomly distributed over the surface (Campbell and Norman, 1998). Kustas and Norman (1999a) describe a relatively simple approach for simulating radiation extinction in clumped canopies with the same exponential equations as used for random canopies by replacing \( LAI \) with the product of a clumping factor \( \Omega(h) \) and \( LAI \) (Chen and Cihlar, 1995). This clumping factor depends on the solar zenith angle, \( \theta_s \).

For computing \( G \), the original formulation from N95 was simply [Eq. (A.9)]

\[ G = c_G R_{N,s}, \]  \hspace{1cm} (A.9)

where the value of \( c_G = 0.35 \) (Choudhury et al., 1987). However, the assumption that \( c_G \) is constant is reliable only for several hours around solar noon (Kustas and Daughtry, 1990).

With \( H = H_s + h_c \) and with the soil and vegetation taken in “parallel” (i.e., the resistance network does not make allowance for interaction between scalar fluxes from the soil and vegetative canopy), the heat fluxes from the soil and vegetation are computed by Eqs. (A.10) and (A.11):

\[ H_s = \rho C_P \frac{T_s - T_h}{R_{N,s}}, \]  \hspace{1cm} (A.10)

\[ H_c = \rho C_P \frac{T_c - T_h}{R_{N,c}}. \]  \hspace{1cm} (A.11)

With \( H_c \) and \( H_s \) taken in “series” (i.e., the resistance network permits interaction between the soil and vegetation heat fluxes, thus influencing the temperature in the canopy air space) yields Eqs. (A.12) and (A.13):

\[ H_s = \rho C_P \frac{T_s - T_{AC}}{R_s}, \]  \hspace{1cm} (A.12)

\[ H_c = \rho C_P \frac{T_c - T_{AC}}{R_c}. \]  \hspace{1cm} (A.13)

where \( T_{AC} \) is the temperature of the air in the canopy, \( R_s \) is the resistance to heat flow in the boundary layer immediately above the soil surface, and \( R_c \) is the total boundary layer resistance of the complete canopy of leaves (see Appendix A in N95) estimated with the wind speed in the canopy air space computed from the equations of Goudriaan (1977). See Figures 1 and 11 in Norman et al. (1995) illustrating the “parallel” and “series” resistance network.

Although soil-surface resistances depend on many factors, a reasonable, simplified equation has been developed (Sauer et al., 1995) where

\[ R_s = \frac{1}{a + bu_s}, \]  \hspace{1cm} (A.14)

In Eq. (A.14), \( a \approx 0.004 \text{ m s}^{-1} \) is the free convective velocity “constant” \( b \approx 0.012 \) and \( u_s \) is the wind speed at a height above the soil surface where the effect of the soil surface roughness is minimal; typically \( 0.05-0.2 \text{ m} \); \( u_s \) is determined assuming an exponential wind profile in the canopy air space with formulations given by Goudriaan (1977) and is summarized in Appendix B of Norman et al. (1995). Kustas and Norman (1999a) refined Eq. (A.14) by including a dependence on free convection from the soil surface so that \( a = 0.0025(T_s - T_{0})^{0.5} \) with a minimum \( a = 0.0025 \text{ m s}^{-1} \). Finally, for \( LE = LE_s + LE_c \) the fluxes are estimated by Eqs. (A.15) and (A.16):

\[ LE_s = R_{N,s} - G - H_s, \]  \hspace{1cm} (A.15)

\[ LE_c = a_{eff} \frac{\Delta}{\Delta + \gamma} R_{N,c}. \]  \hspace{1cm} (A.16)
The Priestley–Taylor parameter $a_{PT}$ is set equal to $\sim 1.3$ (Priestley and Taylor, 1972) for the green part of the canopy, but can be as high as $\sim 2$ under sparse canopy cover conditions (Kustas and Norman, 1999a), $\Delta$ is the slope of the saturation vapor pressure–temperature curve at $T_C$ (Pa K$^{-1}$) and $\gamma$ is the psychrometric constant ($\approx 66$ Pa K$^{-1}$). The fraction of $LAI$ that is “green” or actively transpiring, $f_G$, may be obtained from knowledge of the phenology of the vegetation. If no information is available for estimating $f_G$, then it is assumed to equal unity.

Equation (A.16) only provides an initial calculation of $LE$, and it can be overridden if the temperature difference between the soil–canopy system and the atmosphere is large, causing erroneous flux estimates, such as negative $LE$ or condensation during the daytime period. If the estimated radiometric temperature from Eq. (A.1) is less than the measured $T_b(\phi)$, then the Priestley–Taylor approximation in Eq. (A.16) will tend to overestimate the canopy transpiration rate because the water supply in the root zone is inadequate. Therefore, an iteration procedure will compute $LE$ values below estimates given by Eq. (A.16) until values of $T_C$ and $T_S$ used in Eq. (A.1) agree with the measured $T_b(\phi)$. Further details concerning model convergence issues for the energy budgets of the soil and vegetation in later iterations and the justification for the Priestley–Taylor assumption used in Eq. (A.16) are given in N95 and Kustas and Norman (1999a).

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