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The Role of Scale in Determining Surface Energy Fluxes from Remote Sensing

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11.1 Introduction

Humans have fundamentally altered the mass and energy fluxes between the land surface and the atmosphere. As the world’s population continues to grow, meeting the basic food and water needs of the increased population will require accurate and near-real-time monitoring of water and diminishing resources. The only viable way to do this is through the use of satellite technologies (Wang and Dickinson 2012). However, these observations are collected at certain spatial resolutions that may (or may not) have anything to do with the spatial resolutions of the underlying processes controlling water and energy cycling between the surface and atmosphere. This is one particular aspect of the so-called scaling problem that must be addressed in order to accurately monitor and predict the cycling of water (Anderson et al. 2003; Brunsell and Gillies 2003b; McCabe and Wood 2006; Wu and Li 2009).

When discussing the issues related to scale and scaling, it is essential to have agreed upon definitions for the concepts. Here, we adopt the terminology of Bloschl (e.g., Bloschl 1999), which involves the so-called scaling triplet: extent, spacing, and support. The extent is the overall domain of the study (the image), while the spacing is the distance between consecutive observations (distance between pixels). Support is the area encompassed by an individual observation (resolution). Note that observations, model output, and processes each have their own scaling triplet, and ideally the observational and modeling scaling triplets are chosen to match those of the process triplet. Changing between certain aspects of the scaling triplet is quite easy, for example, decreasing the extent. However, changing
the level of support (aggregation or downscaling) is often not trivial and is often the aspect of the scale problem people are most concerned with.

The scaling triplet of observations is often based on technological and financial considerations, such as what is the highest resolution (spatial and temporal) that can be achieved for a given investment. The modeling triplet can be a similar consideration, particularly for complex models such as general circulation models (GCMs). However, model formulations are often developed at a single scale and may be applied to a wide range of scales. When a model is run at a particular resolution, it is an assumption that all of the model physics are appropriately formulated for that spatial scale. This may induce errors in the model validation if the model is applied at a scale that is not valid. For example, consider the application of Darcy’s law at the spatial resolution of 1° latitude. In the case of remote sensing, this may be a difficult error to assess, as there are few measurement systems (e.g., scintillometers) that are capable of measuring fluxes at the spatial and temporal resolution of satellites, particularly in the case of microwave soil moisture retrieval and other coarse resolution sensors.

It is important to consider that processes that operate across the land surface–atmosphere interface rarely occur at a single scale. In fact, the dominant scales of a process may, in fact, change over time due to the relative contributions of global and regional climate systems, vegetation dynamics, soil formation process, and anthropogenic modification of these processes. Thus disciplines that are focused on the same process but at different scales may develop different (and apparently contradictory) formulations for the same process (Jarvis and McNaughton 1986).

Therefore an observation at a particular scale is really a composite of different processes occurring over a range of time and space. These scales of transport range from microns (water flow through the soil matrix, atmospheric turbulent transport) to global-scale circulation patterns. These different scale processes also interact with one another in nonlinear ways. These nonlinear, multiscale interactions make predictability difficult. This is due to the fact that the insights gained in one location may not be directly transferrable to another location or possibly even the same location at a different time.

The relative importance of the different scales of interaction results in errors when model results are compared to observations that encompass the true multiscale nature of the underlying process. Therefore the goals of this chapter are to (1) highlight the importance of assessing the spatial scale of the inputs and the impact on the resultant surface energy fluxes and (2) discuss how changes in the spatial scale of controlling variables may alter the spatial scaling properties of the derived fluxes.

11.2 The Surface Energy Balance

The source of most of the energy for surface fluxes originates from the difference between incoming and outgoing solar and longwave radiation:

\[
R_n = (1 - \alpha)R_s + \varepsilon (L_u - \sigma T_s^4)
\]  

(11.1)

where \( R_n \) (W m\(^{-2}\)) is the net radiation available to do work at the surface, \( R_s \) is the incoming solar radiation (W m\(^{-2}\)), \( \alpha \) is the surface albedo, \( L_u \) is the downcoming longwave radiation
from the atmosphere (W m$^{-2}$), $\varepsilon$ is the surface emissivity, $\sigma$ is the Stefan–Boltzmann constant, and $T_s$ is the surface radiometric temperature (K).

The net radiation is available to be partitioned into the surface turbulent and conductive fluxes:

$$Rn = H + LE + G$$ (11.2)

where $H$ is the sensible heat transfer (W m$^{-2}$), $LE$ is the latent heat (W m$^{-2}$), and $G$ is the soil heat flux (W m$^{-2}$).

These fluxes are often assumed to be related to a vertical gradient in the associated scalar, for example,

$$H = -\frac{\rho c_p (T_0 - T_a)}{r_a}$$ (11.3a)

$$LE = -\frac{\rho (q_0 - q_a)}{r_q}$$ (11.3b)

where $\rho$ is the air density (kg m$^{-3}$), $T$ is the temperature (K), and $q$ is the specific humidity (kg kg$^{-1}$) at the aerodynamic height (denoted by the 0 subscript) or in the lower atmosphere (denoted by the a subscript). Note that the heights where the aerodynamic and air temperature and humidity are measured are assumed to define the local gradient that determines the magnitude of the surface turbulent flux. There are conditions (e.g., within forest canopies) where countergradient fluxes develop and the above assumption fails.

A complication when using surface remote sensing products for assessing turbulent fluxes between the surface and the atmosphere is the fact that the effective source for the turbulent fluxes is not the actual surface but rather a slight distance above the surface called the aerodynamic roughness length. In addition, each flux has its own roughness length; thus there is a roughness length for heat ($z_0$) and a separate one for humidity ($z_{0q}$). The practical result of this is that the temperature that drives the sensible heat flux ($T_0$) is not equal to the radiometric surface temperature ($T_s$). This is unfortunate in that the surface radiometric temperature is what can be determined from satellite observations.

There have been many attempts to relate the temperatures and the roughness lengths (e.g., Kustas et al. 2007). Generally, this relies on the determination of the $kB^{-1}$ parameter, defined as the logarithm of the ratio of the roughness length for momentum to the roughness length of heat:

$$kB^{-1} = \ln \frac{z_a}{z_{0h}}$$ (11.4)

The roughness length for humidity is often assumed to be the same as that for heat.

Ideally, this parameter could be estimated as a function of vegetation canopy conditions (Lhomme et al. 1994) or as a function of Monin–Obukhov similarity theory (Sun and Mahrt 1995). In reality, however, the $kB^{-1}$ parameter is highly variable in time and space and not easily related to controlling parameters of the surface that could be reasonably detected from satellite platforms (Kustas et al. 2007).
11.3 Surface Heterogeneity and Aggregation

The surface energy balance as outlined above applies to spatially homogeneous surfaces. Heterogeneity in surface properties such as vegetation cover and soil moisture leads to surface patches. When this variability occurs at the subpixel scale, this induces patchiness in the land surface that may be undetected by a satellite sensor. This is problematic from a flux retrieval perspective in that the true areal averaged flux must be aggregated from the individual component fluxes within the pixel and not the areal average of the controlling variables. Unfortunately, the linear average of the controlling variables (e.g., $T_s$) and parameters is exactly what a pixel value obtained from a satellite consists of.

Conservation of energy dictates that the areally averaged flux ($F$) is the linear average of the component fluxes. This necessitates the knowledge of all spatially distributed fluxes ($f(x)$) within the area of interest. Because of issues related to nonlinear averaging (e.g., Jensen’s inequality), the areal averaged flux ($F$) is not the same as the average flux computed from the spatial average of the controlling parameters or variables ($F(X)$):

$$F = f(x) \neq F(X)$$

(11.5)

where the overbar denotes spatial averaging.

This is equivalent to stating that the spatially averaged value of the sensible and latent heat fluxes cannot be computed from the linear average of the resistance terms or the areal average of the temperature over heterogeneous terrain.

As mentioned above, the remote sensing of the surface energy fluxes is the fact that a satellite returns the linear average of the variables (e.g., surface temperature and reflectance) over the area of the pixel. This necessitates the application of a land surface model that uses the areally averaged value of the variable. Depending on the heterogeneity of the land surface, this may or may not cause significant issues with the flux retrieval (Giorgi and Avisser 1997). In general, the more heterogeneous the surface and the coarser the spatial resolution of the sensor, the more likely there are to be errors in the flux retrieval associated with the nature of the input data. This raises the following issue: how does one compute the heterogeneity of the surface and quantitatively determine if this is significant?

11.4 Multiple Scales of Interaction Across the Land Surface–Atmosphere Interface

Most applications of deriving fluxes from remote sensing use a one-dimensional single column model in which the surface interacts with the atmosphere directly above it. Some simple schemes (e.g., single source) assume everything within the pixel is spatially homogeneous. Most schemes assume at least two sources (a bare soil and a vegetated component). This assumes that each pixel interacts with the atmosphere above it independently of the upwind interactions.

The fact that most algorithms for determination of surface fluxes from satellites are one-dimensional (1D) implies that the surface properties as determined from the satellite are assumed to only interact with the atmosphere above the pixel. In fact, in many cases, this
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requires an assumption that the atmospheric properties (temperature, humidity, wind speed, etc.) over the spatial extent of the image are relatively homogeneous. Thus one of the largest issues associated with the spatial scale will be the extent to which the assumption of a 1D framework is valid.

As the spatial scale of the surface features becomes larger, the likelihood of a distinct microclimate developing increases. This has been observed in eddy covariance observations of the surface related to advection of dry air across an agricultural field over relatively small distances (Zermeno-Gonzalez and Hipps 1997). Through the application of a soil–vegetation–atmosphere transfer (SVAT) framework, this assumption of a relatively homogeneous atmosphere implies that each of the surface patches can be modeled independently (Koster and Suarez 1992). If there are several large (of the order of tens of kilometers) patches, then each may be associated with distinct atmospheric conditions that assist in determining the vertical gradient between the surface and the atmosphere, and this assumption may not be valid. A common scenario in which this assumption fails is the presence of mesoscale atmospheric circulations.

Because of the efficient nature of mixing in the atmospheric boundary layer (ABL), there is a height above which the individual patches of the surface patches no longer have a direct influence over the properties in the ABL, and the atmospheric properties are an areal average. This height (really a slow transition to the lack of surface impacts) is known as the blending height (Mason 1988).

The existence of a blending height raises the issue of how the lower atmosphere integrates the properties over a heterogeneous surface. To some extent, this is a function of the atmospheric turbulence in the surface layer [as estimated from the friction velocity, \( u^* \)], but it is also a function of the length scale of the surface heterogeneity and the magnitude of the surface heterogeneity fluctuations. Mahrt (2000) expressed this for conditions of microscale surface heterogeneity as

\[
L_h \ll C_b \frac{U^2}{u^*} h
\]  

(11.6)

where \( L_h \) is the length scale of the surface heterogeneity, \( C_b \) is a blending coefficient, \( U \) is the mean horizontal wind speed (m s\(^{-1}\)), and \( h \) is the height of the atmospheric boundary layer (m).

An important factor to consider here is that the spatial distribution of the surface fluxes is not solely related to the length scale of the surface heterogeneity when computing the land–atmosphere fluxes. It is the interaction between the surface features and the conditions of the lower atmosphere. In addition, the atmospheric conditions are not independent of the surface properties.

The use of large eddy simulation (LES) modeling has been very illustrative of the role of surface heterogeneity on coupled land–atmosphere fluxes. LES studies have shown that the length scale of surface patches will influence the development of the atmospheric boundary layer above and downwind of the patch (Albertson et al. 2001; Brunsell et al. 2011), which thus alters the scalar gradients and the resultant fluxes. The larger the patch is, the higher the influence will extend into the atmosphere. Many smaller patches may each exhibit their own internal boundary layer, above which the atmosphere may be well mixed. The height at which the atmosphere is well mixed is referred to as the blending height, and fluxes above that height are representative of the areal average (Mahrt 2000).

Recent results from LES studies have also shown how the length scales of surface heterogeneity can interact with entrainment and other processes impacting larger-scale
circulations and interactions (Huang and Margulis 2009, 2010). This scale of interaction between the surface and the boundary layer may also help to explain the ubiquitous energy balance closure problem observed with eddy covariance measurements (Huang et al. 2007).

Attempts to characterize the degree of interaction between the surface and the atmosphere have focused on the concept of land–atmosphere coupling (Santanello et al. 2009; Findell and Eltahir 2003). These efforts have been applied to both observational and modeling frameworks to assess the relative roles of boundary layer interactions as a function of surface properties (e.g., wet and dry soil moisture state). While these have not specifically addressed spatial heterogeneity, assessing observational and modeling sensitivities through time and in response to initial surface conditions is essential to understanding the multiscale nature of land–atmosphere interactions.

11.5 Case Study: CLASIC

Determining the relative importance of different spatial and temporal scales to the resultant water and energy fluxes requires understanding the scalewise changes in the controlling variables. This is often quite difficult given a model is used and the data are specified at different scales. This increases the difficulty because it is inherently assuming that the relative variation between input and output does not vary with scale. To examine how different scales of surface vegetation, soil moisture, and radiometric temperature potentially impact the spatial scales of latent and sensible heat exchanges, we examined a case study from the Cloud Land Atmosphere Interaction Campaign (CLASIC) that took place in Oklahoma in the summer of 2007. CLASIC was a campaign that consisted of multiple surface and airborne measurements intended to investigate the role of land surface heterogeneity on boundary layer processes and cloud formation. Unfortunately, the weather during the campaign was generally less than ideal. In order to quantify the impact of scale on the resultant evaporative fluxes, here we focus on two Landsat scenes acquired on June 6 and August 8, 2006, over central Oklahoma. Even though these two Landsat scenes were actually acquired before and after the campaign, they can illustrate a number of issues associated with the determination of surface energy and mass fluxes from satellites.

Landsat data used for this analysis were obtained without terrain correction and were corrected for atmospheric effects using Modtran and radiosonde profiles. The Simsphere SVAT model (e.g., Brunsell and Gillies 2003a,b; Brunsell et al. 2008) was utilized for the mapping of the remotely sensed data into the surface energy fluxes using the methodology described next.

11.5.1 The “Triangle” Method

The “triangle” method is used to relate the remotely sensed vegetation index and land surface temperature to the resultant energy fluxes (Gillies et al. 1997; Carlson 2007; Petropoulos and Carson 2011) The vegetation index is the fractional vegetation (Fr), which is a scaled version of the normalized difference vegetation index (NDVI):

\[
Fr = \left( \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right)^2
\]  

(11.7)
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where NDVI, is the pixel value of the NDVI and the max and min subscripts refer to the maximum and minimum values of NDVI in the scene.

When the Fr is plotted against the land surface temperature, a general triangular shape usually results. For example, Figure 11.1 illustrates the joint probability density plots between Landsat derived $T_s$ and Fr for June 3 and August 6, 2007, over the CLASIC field site. This triangle is associated with several important features of the land surface, including a warm, nonvegetated area, progressing along a warm edge to a relatively warm fully vegetated region. The cool edge exhibits a relatively constant temperature that usually corresponds closely with the air temperature. For a given value of vegetation cover, there is a range of land surface temperatures observed in a given scene. These temperatures are assumed to be due to the variation in the near surface soil moisture ($M_0$).

As the near-surface soil moisture decreases, evapotranspiration begins to decrease because of water limitation. This, in turn, results in an increase in the radiometric temperature as more of the net radiation becomes partitioned into sensible heat. A SVAT scheme can be calibrated using additional information (e.g., a radiosonde profile) to match limiting cases of the water limitation (i.e., the corners of the triangle). The model is iterated over all possible combinations of initial soil moisture and vegetation fraction. The modeled radiometric temperature and surface energy fluxes are output at the time of satellite overpass, and a polynomial regression is constructed to relate the surface temperature and vegetation fraction to the fluxes:

$$F_x = \sum_{i=1}^{3} \sum_{j=1}^{3} a_{i,j} T_i Fr^j$$

where $F_x$ is the flux of interest (latent heat LE, sensible heat $H$, etc.). This equation is then applied to the remotely sensed temperature and vegetation to determine the flux from the satellite imagery.

FIGURE 11.1
(See color insert.) Joint probability density plots for the Landsat images for (a) June 3 and (b) August 6, 2007, over the CLASIC field site in central Oklahoma.
11.5.2 Assessing Scale Issues

One possible way of understanding the relative importance of land surface heterogeneity is through the use of information theory metrics such as Shannon entropy, mutual information content, and relative entropy (Brunsell et al. 2008). These metrics are used to assess the amount of information within the observed signal, as well as the information redundancy and transfer between different data series.

The first step to examining these metrics was to examine the role of spatial scale on the remotely sensed data itself. For this purpose, we employed the technique of low-pass filters conducted with wavelet decomposition. This is similar to previous work conducted surrounding the Fort Peck Ameriflux site in Montana (Brunsell and Anderson 2011). This technique allows us to determine how the image would appear with coarser spatial resolutions by progressively removing the higher-frequency information. We utilized a dyadic decomposition through seven levels of decomposition, resulting in resolutions of 200 m to 12.8 km. Figure 11.2 shows selected scales of decomposition for the fractional vegetation, surface temperature, as well as the modeled latent heat fluxes for the August 6 image. For these illustrative purposes, we have only shown selected scales, corresponding to 200, 800, and 3200 m.

These images support the general idea of a reduction in variance with increasing spatial scale. While many features are collocated (e.g., more vegetated locations tend to have lower surface temperatures), these correlations are not perfect and there are some differences in the transition from fine to coarse resolution. However, it is difficult to quantify these relationships solely from visually inspecting the decomposed images.

In order to quantify the variability in the remotely sensed fields as well as the model output as a function of spatial scale, we calculated the wavelet spectra for each date. In addition, we can investigate the potential anisotropy in the images by calculating the wavelet spectra in the horizontal, diagonal, and vertical directions of the two-dimensional image. Figure 11.3 shows the three directional spectra for the $M_0$ and the derived LE flux for both the June and August images. The dominant length scale is defined as the scale at which the wavelet variance is highest. For most of these data fields this is of the order of 1600 m for both days. However, there is a clear difference in the anisotropy between the two dates. For example, consider the near-surface soil moisture $M_0$ on June 6 (Figure 11.3a), where each directional spectrum exhibits a different length scale ranging from 400 to 1600 m. While in the August case (Figure 11.3c), each direction is more or less the same.

The question then becomes, to what extent does this anisotropy in the controlling fields impact the spatial variability of the LE flux? This can also be seen in Figure 11.3b and d. The variability with spatial resolution on June 6 does not obviously match any of the controlling variables. Consider the vertical spectra, the LE flux peaks at 1600 m that most closely matches the pattern observed in the Fr field (not shown). While for the August case, the fields are mostly similar for the diagonal spectra, the resultant shape of the spectra most closely matches the $T_s$ rather than the Fr. This could imply a shift in the physical dynamics controlling the evaporative process between these two dates.

While the wavelet spectra can illustrate the dominant length scale of the surface field and the associated anisotropy, it does not necessarily inform how much of the resultant signal (e.g., the LE flux) is due to the scalewise variability in the input fields. To ascertain this, we combined the wavelet decompositions with the information theory
FIGURE 11.2
(See color insert.) Wavelet decompositions of the August 6, 2007, Landsat imagery (a), fractional vegetation (%) (b), and surface temperature (K) (c) latent heat flux (W m⁻²) for selected scales (A) 200 m, (B) 800 m, and (C) 3200 m.
metrics entropy and relative entropy. This is done following the methodology developed previously (Brunsell et al. 2008; Brunsell 2010), where the Shannon entropy is

\[
I = \sum_{i=1}^{n} p(x_i) \log(p(x_i))
\]

(11.9)

where \( I \) is the entropy and \( p \) is the probability that the data value \( x \) falls within a histogram bin \( i \). The entropy is a measure of the total information contained in the data series. The relative entropy \( \text{Re}(x,y) \) is a measure of the additional information needed to characterize \( x \) given the amount of information contained in \( y \), based on their respective probability functions \( p \) and \( q \):

\[
\text{Re}(x,y) = \sum_{i=1}^{n} p_i \log \left( \frac{p_i}{q_i} \right)
\]

(11.10)

FIGURE 11.3
Wavelet spectra in the horizontal, vertical, and diagonal directions from the Landsat imagery for the (a, c) soil moisture and (b, d) latent heat flux for (a, b) June 3 and (c, d) August 6 images.
These metrics provide insight into the information ‘gained’ from each scale, with the higher entropy values showing the most uniform distributions and having the highest information content. The spatial entropy spectra are shown in Figure 11.4a and b for the LE and the $H$ fluxes, respectively. The LE shows a decrease in the entropy at almost all scales from June 3 to August 6. The $H$ spectra, on the other hand, are generally the same up to approximately the 2000-m scale, at which point the spectra decline for both days with the June 3 case being lower. This illustrates that the scaling behavior of different fluxes cannot be assumed to be the same, even for the same scene.

**FIGURE 11.4**
Information entropy for (a) latent heat flux and (b) sensible heat flux for June 3 and August 6 Landsat images over the CLASIC field campaign area. Panels (c) through (h) show the relative entropy between the controlling parameters of fractional vegetation, surface temperature, and soil moisture for each of the fluxes for each day.
In order to ascertain how the scalewise variability in the controlling fields of $T_s$, $Fr$, and $M_0$ relate to the changes in the fluxes across scale we utilized the relative entropy (Re) spectra. In this application, the relative entropy quantifies how much additional information is necessary to capture the output field given the input field. Thus the Re between the LE flux and the Fr would show to what extent we can predict the LE from the information contained in a particular scale of the Fr. Higher values indicate more information is needed, and therefore the ability to predict the total flux is more limited at that scale of the input data.

The Re for the LE fluxes are shown in the first column of Figure 11.4 (panels c, e, and g). For the June 3 date, the Fr exhibits higher Re in the intermediate spatial scales (e.g., 1000 m), with lower values at the extremely small and large scales. The Re($LE$, $T_s$) shows a general decline in the Re from the smallest to the largest scales. The soil moisture influence is generally the same as the Fr. The August 6 image shows a different dynamic, where the Re($LE$, Fr) and Re($LE$, $M_0$) are relatively flat across all scales, indicating that each scale is relatively equally influenced by the Fr and $M_0$. The relative entropy with $T_s$ shows a general decrease relative to the earlier image and is constant up to approximately 3200 m.

The sensible heat behaves differently with respect to the influence of the controlling variables across scale. The Re($H$, Fr) is generally the same for the two dates and is highest at the smallest scale. The influence of $T_s$ on $H$ shows a generally decreasing Re similar to the LE variability for June 3, but the August 6 case shows a high Re in the intermediate scales (approximately 1600 m). The role of soil moisture changes depending upon the date, where the June 3 case shows a high value in the smallest scale and decreases to about 800 m, above which it is constant. While on August 6, the Re is basically constant with scale.

These results indicate that the dominant length scales are on the order of 1600 m for most cases, but the contribution to the fluxes by the dominant input variables changes depending on the date. To first order, the influence of the surface temperature is higher at the larger spatial scales (indicated by lower relative entropy), while the influence of the vegetation is the reverse. This is in agreement with prior results from the Southern Great Plains 1997 experiment (Brunsell and Gillies 2003a). However, this influence is not constant over time, which implies that the ability to scale fluxes based on a parameterization of the controlling variables is not likely (Brunsell and Anderson 2011).

### 11.6 Discussion and Recommendations

One of the significant findings of the above case study is that the role of surface heterogeneity varies depending on the time of data acquisition. More importantly, the relative contribution of the controlling variables such as soil moisture and vegetation varies in time and may be different for the different components of the surface energy balance. Note that this is not to be confused with simply saying that the seasonal pattern in time is important. This is illustrative that the role of the spatial length scales of the surface fields is changing in conjunction with the seasonal dynamics. Other research has also found that these patterns change in time and are also a function of the satellite used to quantify these patterns (Brunsell and Anderson 2011).

This is perhaps indicative of the nonlinear impacts between vegetation, soil, and boundary layer processes. Each of these factors is changing with their own timescales of variability and each have a relatively important role on the partitioning of surface energy fluxes.
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When we consider the goal of quantifying the transfer of mass and energy between the surface and atmosphere, we must address how the processes of evaporation and sensible heat are a combination of processes acting at multiple spatial and temporal scales. It is well known that soil moisture and vegetation interact at a wide range of temporal scales to alter near-surface moisture and heat transfer (Katul et al. 2007; Seneviratne et al. 2010). At interannual timescales, woody encroachment and other changes in the vegetation can impact the surface pattern and thus directly alter the mass and energy fluxes (Huxman et al. 1986).

Changes over time with respect to vegetation phenology, seasonal patterns in precipitation and soil moisture, and longer-term soil formation processes all alter the timescales of surface processes. The fact that these processes are also varying spatially across the landscape implies that the spatial scaling characteristics are also temporally varying. Therefore any study that quantifies the spatial scaling characteristics at a single time may be of limited utility (Brunsell and Anderson 2011). There is additional evidence that changing the spatial resolution may result in more errors in modeling of vegetation processes (Kucharik et al. 2006).

Interactions between surface heterogeneity and processes above the boundary layer may also play an important role in the maintenance of preferred soil moisture–precipitation feedback regimes. Soil moisture–vegetation interactions have also been shown to be linked in particular regions to strong feedback with precipitation patterns both using remote sensing (Brunsell 2006) and modeling approaches (Koster et al. 2004; Jones and Brunsell 2009). The physical mechanisms underlying these feedback regions are linked to local evaporative fraction, energy balance partitioning, albedo, etc., which thus aid in cloud formation and precipitation (Huang and Margulis 2011).

The hydrological cycle is known to function at a wide range of scales from the molecular to the global. In operational settings, it is often necessary to choose specific resolutions while implicitly or explicitly ignoring the impacts of different scales. For example, in the case of monitoring evapotranspiration and other surface energy budget terms, it is often assumed that groundwater dynamics can be neglected. However, recent results have shown a direct impact of groundwater on surface fluxes (Kollet and Maxwell 2008). Thus longer-term geological processes may ultimately be important for truly understanding surface fluxes and thus the ability to quantify these interactions from satellite platforms even at short timescales. Ultimately, the only way to truly know if these interactions are important is to quantify the impact and then make the decision.

As we enter the anthropocene, it is essential that we also focus explicitly on the role of humans on altering the dynamics of land–atmosphere interactions. We have fundamentally altered the nature of hydrological cycling (Wohl et al. 2012) and have also altered many of the timescales associated with these cycles.

The human-induced nature of land cover change also directly impacts all of the processes outlined in this chapter (Foley et al. 2005; Feddema et al. 2005). One role for the use of remote sensing for quantifying these impacts is an explicit focus on the role of land cover and land cover change. For example, consider the case of irrigated agriculture (Twine et al. 2004). If we consider agricultural cropping selection patterns that are altered in response to energy needs (e.g., biofuel production), this will ultimately affect the water use requirements of the vegetation (VanLoocke et al. 2012), thus impacting irrigation, surface soil moisture, evapotranspiration, atmospheric humidity and precipitation, and all of the other impacts of the hydrological cycle. While the local impact of irrigation on the surface energy balance may appear quite easy to monitor from satellites in that it raises the evaporation to nonwater limited conditions, this has profound impacts on the meso- to regional-scale circulations in the region of irrigation (Adegoke et al. 2003). Irrigated sites...
can quickly create local oasis effects and profoundly alter the microclimates surrounding the area as well as the circulations. The microclimatic alterations to saturation deficit and air temperature may be quite difficult to ascertain from surface satellite observations, making the quantification of the surface fluxes problematic.

A secondary example of anthropogenic alteration of the landscape that may prove problematic for surface flux determination from satellite is the urban environment. As the world’s landscape becomes more urbanized (Elvidge et al. 2004), understanding the role of the urban surface energy balance will become more vital. While previous efforts at addressing the nature of the surface energy balance in urban environments points out that a lot of progress has been achieved (Arnfield 2003), there is still a fundamental scale problem between the scale of urbanization and the ability to detect this from satellite platforms. Jin and Dickinson (1999) discussed the schemes to integrate urban effects in the land surface models using remote sensing techniques and concluded that satellite-observed urban information has highly potential simulated urban effects in climate models.

Even with high-resolution satellite data, there is still the issue of the interaction between the length scales of the surface and the atmosphere as outlined above. These interactions in urban environments also extend themselves well beyond the urban pixels through the urban heat island as well as alteration of the downwind precipitation patterns, etc.

The examples of irrigated agriculture and urban environments are particularly problematic for satellite monitoring due to the spatial scale of the land surface modification (i.e., the length scale of heterogeneity) but also the magnitude of the alteration on the local microclimate relative to the surrounding area. The spatial variances of the surface and lower atmosphere conditions increase with the intensity of the modification, often at incredibly fine spatial scales. Accurately quantifying the impacts on the surface energy balance requires understanding the length scale of the surface heterogeneity and the time-scales of the surface alteration on surface properties like thermal inertia, heat capacity, etc., that all directly impact the partitioning of the net radiation into the component surface energy fluxes.

The surface alterations in these cases lead directly to profound impacts on the atmospheric conditions. Not only do the changes in the surface fluxes lead to changes in air temperature and saturation deficit, but they also induce circulations that will involve the advection of dry (moist) air over the irrigated (urban) area. This advection is induced from the changes in density over the area and the increase in buoyancy. This impact will be a result of the horizontal gradients in moisture and temperature that potentially can be estimated from the satellite observations of the surface.

From these examples, we can suggest that to increase the accuracy of remote sensing of the surface energy balance we should attempt to consider the role of spatial configuration of the surface patches on the pixel scale fluxes. Note that we are not referring to subpixel aggregation here but rather that airflow from adjacent pixels can alter the microclimate within a pixel. As discussed previously, LES simulations have shown that that magnitude and the configuration impacts the surface fluxes, and while the satellite can quantify the surface magnitude, little work has been done on explicitly incorporating remotely sensed land conditions into LES (Huang and Margulis 2010; Brunsell et al. 2011; Albertson et al. 2001).

Rather than conduct LES studies over all areas of the world using Landsat data, we recommend an explicit focus on the length scales of surface heterogeneity and the relationship between the surface variance and the induced variance in the atmospheric properties. Of course, the induced variability downwind will be a function of the spatial scale of the atmospheric grid, local conditions, etc. This would result in empirical scaling relationships.
such as those of Equation 11.6, which will vary in time and place. However, through enough studies, it may be possible to generalize these scaling relationships as a function of seasonal variation and dominant land cover class.

The above discussion often assumes that the local scale fluxes are known, and the difference between a ground-based observation and a remotely sensed estimate is due to various scale issues associated with the change in resolution. While this is true, the actual comparison of surface and satellite-based estimates is nontrivial. Surface observations such as eddy covariance towers and scintillometers have a resolution of their own. This resolution must be accounted for when comparing a surface observation to a satellite pixel. This usually consists of either (1) a direct comparison between the pixel in which the surface observation is located or (2) the use of a footprint model (e.g., Schmid 2002). This allows a weighting to be applied to the appropriate pixels and is most useful when the resolution of the satellite is finer than the area of the surface observation. Thus the surface observation encompasses more than one pixel. In the case of lower resolution satellites (e.g., MODIS), the entire footprint of the surface observation may be encompassed within a single pixel. Without additional information on the subgrid variability of that pixel, there is probably little gained by the application of a footprint model in these cases.

11.7 Conclusions

This chapter has highlighted some of the theoretical and practical considerations when attempting to address the scale issue for satellite monitoring of the surface energy balance. These issues range from the mismatch in theoretical scale of the equations to the practical scale of application at the satellite pixel, issues pertaining to the micrometeorological substitution of the radiometric surface temperature for the aerodynamic temperature, multiscale interactions between disparate processes governing vegetation, soil and atmospheric processes, as well as the interaction between spatial configuration and inducing mesoscale circulations. An example of a methodology for quantifying these variations was outlined using data from a field campaign that highlights how the dominant surface properties governing land–atmosphere exchanges can vary with date of satellite data acquisition. Ultimately, these results illustrate that the routine monitoring of water and energy fluxes from satellite data requires careful consideration of both surface and atmospheric interactions. We propose that future research should specifically focus on understanding the interaction as a function of spatial length scales and the variance of induced surface and atmospheric properties for determining scaling relationships that can hopefully allow enhanced monitoring of the water and energy fluxes using surface optical and thermal satellite data.

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