EFFECTS OF SPATIAL VARIABILITY ON THE SCALING OF LAND SURFACE PARAMETERIZATIONS

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Abstract. Understanding and modelling physical and dynamical processes over heterogeneous land surfaces have become a central focus of many recent studies. There is a considerable debate, however, over how to represent the effects of spatial heterogeneity in mesoscale and global scale models. Here, a computationally efficient analytical approach is presented to evaluate scaling properties of land surface representations. It is shown that the effects of spatial variability may not be negligible for commonly encountered land surfaces and associated parameterizations. Second-order correction terms involving variances of the parameters and covariances of each pair of land surface parameters are developed to account for the effects of heterogeneity. Using this analytical approach, we show that the detail of spatial heterogeneity may not be important for the infrared radiation and reflected solar radiation from the surface, while sensible and latent heat fluxes are shown to be sensitive to heterogeneity. Assumptions related to different parameterizations for the same physical process could potentially lead to different inferences regarding the influence of spatial heterogeneity. The proposed approach, however, is capable of identifying the role of different parameterizations in estimating the influence of spatial heterogeneity. These analytical results are consistent with the results of several recent numerical and field experiments that deal with the effects of small-scale heterogeneity in land surface characteristics.

Key words: Surface heterogeneity, Scaling, Land-surface parameterization, Scale invariance, Aggregation and disaggregation.

1. Introduction

It is now recognized that adequate representation of land surface processes is important for the accurate description of regional and global climate. The land surface is usually very heterogeneous at the size of typical mesoscale and climate model grid blocks. This heterogeneity has not been fully represented in commonly used mesoscale and climate models. As a result, characterization of small-scale land surface heterogeneity in modelling the land-atmosphere system has become a central focus of many recent studies. There is a considerable debate, however, over the influence of subgrid scale land surface heterogeneity on the grid-scale response, and over how to parameterize the effects of spatial heterogeneity in atmospheric models.

In recent years, several approaches have been proposed to represent land surface heterogeneity in mesoscale and climate models. One approach is to increase the resolution of the model grid at the ground surface. Such an approach divides the model grid into finer resolution subgrid elements and estimates the surface

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fluxes at the subgrid scale (e.g., Dickinson et al., 1989; Koster and Suarez, 1992). Dickinson et al. (1989) used general circulation model (GCM) output to provide the horizontal boundary conditions needed for a regional atmospheric model with much higher temporal and spatial resolution (1.5 min; 60×60 km^2). They found that intragrid topography and land surface properties strongly influence the distribution of precipitation at the mesoscale, and that the nested GCM-mesoscale model provides a more realistic representation of precipitation than the original GCM. Koster and Suarez (1992) assumed that each subgrid element (hereafter, subgrid) interacts with the atmosphere independently, with atmospheric forcings at the first model level kept the same for all subgrids within a grid. For each subgrid, the land surface model is applied to assess the surface temperature and humidity, and turbulent fluxes to the atmosphere. The model responses at the grid level are calculated by averaging over all subgrids within a grid block. The computational requirement of running a mesoscale model (Dickinson et al., 1989), or land surface model for each subgrid (Koster and Suarez, 1992), can be an order of magnitude larger than that required to run the associated GCM. At present, the limitation imposed by the availability of computer resources inhibits the practical utilization of this otherwise promising approach (Gao and Sorooshian, 1994). Furthermore, this approach still cannot resolve all subgrid-scale heterogeneity because the subgrid size is still much larger than correlation scales of many land surface processes.

Another approach is to determine the effect of land surface heterogeneity on the surface fluxes by using so called scale invariant land surface parameterizations. A scale invariant parameterization uses grid level mean values of parameters, but promises to provide a good estimate of grid level response or output. Sellers et al. (1992) and Hall et al. (1992) claim that, based on the analysis of the FIFE (First ISLSCP (International Satellite Land Surface Climatology Project) Field Experiment) data, land-atmospheric models are almost scale invariant. However, the relatively homogeneous FIFE site might hinder the generalization of this conclusion. Another scale invariant approach is to define the effective parameter values at grid level, so that the land surface parameterizations, which were developed at a local or point scale, are still valid at the grid scale. The effective value of a given parameter must be determined for each application, and so is not unique (Lhomme et al., 1994). For example, an effective surface temperature can be estimated from the sensible heat flux parameterization. Another estimate of the effective surface temperature can also be obtained from the surface longwave emission parameterization. Thus for a single parameter, different parameterizations can lead to different effective parameter values.

Several studies have used the effective roughness length to account for the effects of surface heterogeneity. To derive an effective roughness length for a heterogeneous surface, Wieringa (1986) introduced the blending height concept that has been intensively studied in the literature (e.g., Mason, 1988; Claussen, 1991; Blyth et al., 1993; Claussen, 1995a, b; von Salzen et al., 1996). The blending height is a scale height for the heterogeneous surface, above which the atmospheric flow does not depend on the heterogeneous surface features. Thus, the atmospheric properties above this height will be homogeneous and do not depend on the specific horizontal locations. The blending height concept is quite useful in the formulation of the effective roughness length for the estimation of surface fluxes from heterogeneous surfaces. Mason (1988) provided an estimate of the blending height based on the horizontal scale of the surface heterogeneity. Later, Claussen (1990) extended Mason's approach to the definition of effective drag coefficients of momentum and passive admixtures, and Wood and Mason (1990) extended the blending height concept into flux estimation in non-neutral conditions. The blending height concept has been incorporated in various numerical studies in regard to the significance of the surface heterogeneity (Claussen, 1991; Blyth et al., 1993; Claussen, 1995a, b; von Salzen, 1996; Grotzner et al., 1996). The concept of the blending height is applicable when the scale of the surface heterogeneity is small (a few kilometres) and the lower atmosphere is not unstable. As Grotzner et al. (1996) argued, when the scale of the heterogeneity becomes larger and the lower atmosphere is more unstable, the blending height will tend to be well above the convective boundary layer. Then the similarity law for the flux estimation will not be applicable using this blending height. A detailed review of the blending height concept and its application to characterizing the effect of surface heterogeneity may be found in Raupach and Finnigan (1995) and references therein.

In an attempt to minimize computational demand, the statistical-dynamical approach is also used to represent subgrid-scale heterogeneity. A common approach is to use the probability density functions to describe subgrid-scale spatial variability of certain variables and derive probability density functions for an aggregated response (Entekhabi and Eagleson, 1989; Famiglietti and Wood, 1991). Bonan et al. (1993), Wood and Lakshmi (1993) and Li and Avissar (1994) demonstrated the influence of the spatial heterogeneity of land surface characteristics on the surface fluxes by using the statistical distributions for the land surface parameters. Bonan et al. (1993) and Li and Avissar (1994) found that the heterogeneity of the land surface is important to the grid level sensible and latent heat fluxes, whereas Wood and Lakshmi (1993) found that the latent heat flux is not particularly sensitive to the heterogeneity. In fact, Bonan et al. (1993), Wood and Lakshmi (1993) and Li and Avissar (1994) used an approach similar to Koster and Suarez (1992), but the parameter values were specified using statistical distributions. Thus, similar computational demands are inherent in these statistical-dynamical approaches as well. For example, Li and Avissar (1994) used a total of 5,580,900 steady state simulations to conclude, in general, that the latent heat flux was the most sensitive, while the radiative flux emitted by the surface was the least sensitive, to spatial heterogeneity.

In this paper, we present an analytical approach to evaluate the scale-invariant properties of different land surface parameterizations. This approach can also be used to develop parameterizations that include effects of land surface heterogeneity. In Section 2, we provide some definitions that have specific meanings in this paper.

In Section 3, we present a systematic procedure to test the adequacy of scale invariance in land surface modelling. Some applications of our methodology are presented in Section 4, and concluding remarks are given in Section 5.

2. Definitions

A few terms used in this paper have a specific meaning, and we define them here. A heterogeneous land surface within a grid square may be viewed as a collection of land surface elements, called ‘subgrids’, ‘patches’, or ‘tiles’. In this paper, subgrid, patch, and tile are used interchangeably; they represent a small area that can be assumed to be homogeneous.

Map is a function, or model, or algorithm, or parameterization that takes a set of parameters as input and produces an output (or response). For example, the bulk transfer parameterization of sensible heat is a map. This map consists of a representation of sensible heat flux that includes air density, transfer coefficient, first model level wind velocity and temperature, and surface temperature as input and produces the sensible heat flux from the surface as an output.

In a lumped model, the system is spatially averaged, or regarded as a single point in space without dimensions. For example, many lumped models of the rainfall-runoff process treat the precipitation input as uniform over the watershed and ignore the internal spatial variation of watershed flow. On the other hand, the distributed model considers hydrologic processes taking place at various points in space and defines the model variables as a function of spatial dimensions.

Here, a lumped representation takes grid scale parameter values as input, and produces a grid level output or response. The output from a lumped map is a grid level output. By a lumped model, we mean that the grid is spatially homogeneous with regard to its inputs, parameters, and outputs (Figure 1, right part).

A distributed map calculates the grid-level response by first dividing the grid into a number of subgrids that can be assumed to be homogeneous. Then the response of each subgrid is aggregated by a suitable kernel (e.g. areal weighted average) to get the grid-level output. Thus, a distributed model accounts for the spatial variability of inputs, parameters, and outputs within the grid. The estimation of the grid-level response by a suitable kernel from each subgrid is referred to as aggregation (Figure 1, left part).

A scale invariant land surface map means that the empirical relationship developed from point observations can be used for large areas (e.g., at the mesoscale or GCM grid scale). A scale invariant map will produce a grid-scale response if we use average parameters over the grid as input. For example, if we use grid average values of albedo and surface temperature, a scale invariant reflected solar radiation map will produce grid-level reflected solar radiation. Quasi-scale-invariant map means that the resulting error from using a lumped map to estimate grid-level response will be small.

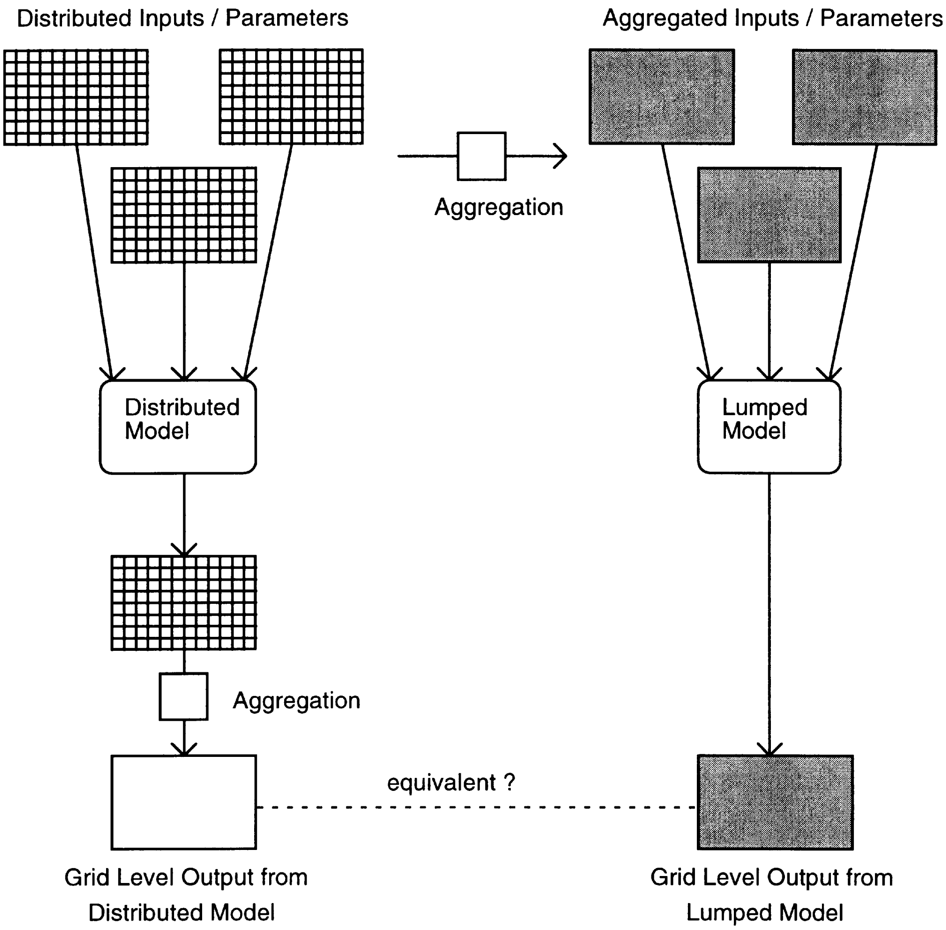

Figure 1. Scheme for aggregation and scaling in land surface modelling. The left part is for the distributed model which assumes that the grid block is subdivided into many homogeneous subgrids and the model is applied to each subgrid to get distributed model responses. Later, an aggregation kernel is applied to these distributed responses to obtain the grid level output. On the other hand, in the right part the distributed model inputs and parameters are aggregated first to get grid level inputs and parameters, then the model is used to get the grid level estimate. If two estimates are equivalent, the model is scale invariant.

3. Analysis of Scale Invariance: An Analytical Approach

An important problem in land surface modelling is the identification of relationship(s) between point scale measurements and grid-level response. If a map is valid for a point scale, can we use this map at the scale of a mesoscale or GCM grid block? Under what condition is the map scale invariant? In order to answer these questions, we begin our discussion with a map at the point scale. Then, we will present two conditions regarding properties of the scale invariant map.

Let $f(P_1, P_2, \ldots, P_n)$ be the joint density function of parameter set $\{P_1, P_2, \ldots, P_n\}$ over a model grid (e.g., GCM grid), then the fractional area that has the same set of parameters $\{P_1, P_2, \ldots, P_n\}$ in the range of $\{\Delta P_1, \Delta P_2, \ldots, \Delta P_n\}$ will be

$$f(P_1, P_2, \ldots, P_n) \cdot \Delta P_1 \Delta P_2 \cdots \Delta P_n, \tag{1}$$

where ΔP_1, $\Delta P_2, \ldots$, and ΔP_n are intervals of parameters. We assume here that each parameter is discretized into Q equal intervals. This is equivalent to dividing a GCM grid into Q patches, with fractional area corresponding to the frequency of each interval as defined by (1).

Let the output from the map at a patch q be G_q; for the parameter set at the patch q $\{P_1, P_2, \ldots, P_n\}_q$ of a specific map, we have

$$G_q = \text{map}(\{P_1, P_2, \ldots, P_n\}_q). \tag{2}$$

Then the grid scale output will be

$$\begin{aligned} \overline{G_d} = \sum_{q=1}^{Q} & \text{map}(\{P_1, P_2, \ldots, P_n\}_q) \cdot f(\{P_1, P_2, \ldots, P_n\}_q) \\ & \times \Delta P_1 \, \Delta P_2, \ldots, \Delta P_n. \end{aligned} \tag{3}$$

The subscript "*d*" indicates that the grid-scale output is aggregated from the output of a distributed model. Taking the limit to the above equation with respect to Q (this is equivalent to dividing the GCM grid block into finer subgrids), we have

$$\begin{aligned} \overline{G_d} = \int\int \cdots \int & \text{map}(P_1, P_2, \ldots, P_n) \cdot f(P_1, P_2, \ldots, P_n) \\ & \cdot \mathrm{d}P_1 \, \mathrm{d}P_2 \cdots \mathrm{d}P_n. \end{aligned} \tag{4}$$

This is a generalized formulation for the estimation of grid-level quantities by taking subgrid-scale heterogeneity into account. Recent studies have addressed the influence of subgrid-scale heterogeneity on the grid-scale response by using a probabilistic framework. For example, by assuming an exponential distribution for the point precipitation, and gamma distribution for the soil moisture content, Entekhabi and Eagleson (1989) derived explicit expressions for surface runoff and evapotranspiration, and evaluated the influence of the spatial heterogeneity of precipitation and soil moisture content on the grid-scale surface runoff and evapotranspiration. Their analysis assumed mutually independent statistical distribution for soil moisture and precipitation. For short time steps generally used in atmospheric model integration, spatial patterns of precipitation and soil moisture are likely to be highly correlated (Schaake, 1994). Jackson and Schmugge (1989) also noted that for large area studies rainfall driven soil moisture variations play an important role in the estimation of surface flux. Thus, we need to include interactions between atmospheric processes and land-surface types within a grid. Equation (4) is an example of such a general joint density function. The lack of knowledge of the joint parameter density function of a map, however, makes practical use of Equation (4) difficult. Nonetheless, Equation (4) may be used to elucidate some properties of a scale invariant map.

Let the density function for the ith parameter be $f_i(P_i)$, then the grid-scale value of this parameter, which is the grid average of this parameter, will be

$$\overline{P_i} = \int P_i f_i(P_i)\,\mathrm{d}P_i. \tag{5}$$

Let $\{\overline{P_1}, \overline{P_2}, \ldots, \overline{P_n}\}$ be the grid-scale parameter set. The traditional approach assumes that the point map is valid at the grid scale; then, the lumped output over a grid can be estimated as

$$\bar{G} = \mathrm{map}(\overline{P_1}, \overline{P_2}, \ldots, \overline{P_n}). \tag{6}$$

If the map is scale invariant, Equations (4) and (6) will lead to the same grid-scale output. There are at least two conditions under which a scale invariant assumption will be appropriate. First, *if the parameters are homogeneous over the grid, then the map is scale invariant;* second, *if the map is a linear combination of inputs and parameters, then the map is scale invariant.*

These two conditions are fairly straightforward to understand, although they are perhaps the most difficult conditions to satisfy for the naturally occurring surface and typical land surface parameterizations. Recent research on the scaling properties of land surface processes recognizes that the nonlinearity of land surface parameterizations might lead to the difference between the aggregated output from a distributed map and the output from a lumped map (Sellers et al., 1992; Hall et al., 1992; Wood and Lakshmi, 1993; Li and Avissar, 1994).

For the land surface in a mesoscale or GCM grid, either of these two conditions will be difficult to satisfy. Thus, theoretically, it may be difficult to develop a simple a scale invariant map for scaling up in the land surface parameterizations. However, if the error is very small between the aggregated output from a distributed map and the output from a lumped map, a quasi-scale-invariant relationship may still be feasible. Such a quasi-scale-invariant map would be very useful for land surface modelling, since the surface fluxes can be estimated by using lumped models and the computational burden and memory storage greatly reduced. Let us divide a GCM grid into m equal size subgrids and let $\{P_1, P_2, \ldots, P_n\}_k$ be the parameter set for a map at subgrid k, and $\{\overline{P_1}, \overline{P_2}, \ldots, \overline{P_n}\}$ be the average parameter set for that map over the grid. Neglecting 3rd and higher order terms, one can estimate the output at subgrid k using small perturbation theory, as

$$\mathrm{map}(\{P_1, P_2, \ldots, P_n\}_k) \approx \mathrm{map}(\overline{P_1}, \overline{P_2}, \ldots, \overline{P_n})$$

$$+\left[(P_1-\overline{P_1})_k\frac{\partial}{\partial P_1}+(P_2-\overline{P_2})_k\frac{\partial}{\partial P_2}+\cdots+(P_n-\overline{P_n})_k\frac{\partial}{\partial P_n}\right]$$
$$\times \text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n})$$
$$+\frac{1}{2}\cdot\left[(P_1-\overline{P_1})_k\frac{\partial}{\partial P_1}+(P_2-\overline{P_2})_k\frac{\partial}{\partial P_2}+\cdots+(P_n-\overline{P_n})_k\frac{\partial}{\partial P_n}\right]$$
$$\times \text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n}). \tag{7}$$

Then the aggregated output over the grid from a distributed map is

$$\overline{G_d}=\frac{1}{m}\sum_{k=1}^{m}\text{map}(\{P_1,P_2,\ldots,P_n\}_k)$$
$$\approx \text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n})$$
$$+\frac{1}{m}\sum_{k=1}^{m}\frac{1}{2}\cdot\left[(P_1-\overline{P_1})_k\frac{\partial}{\partial P_1}+(P_2-\overline{P_2})_k\frac{\partial}{\partial P_2}+\cdots+(P_n-\overline{P_n})_k\frac{\partial}{\partial P_n}\right]^2$$
$$\times \text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n}). \tag{8}$$

The lumped output over the grid is

$$\bar{G}=\text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n}). \tag{9}$$

The difference between aggregated output from a distributed map and lumped output is

$$\overline{G_d}-\bar{G}\approx\frac{1}{m}\sum_{k=1}^{m}\frac{1}{2}\cdot\left[(P_1-\overline{P_1})_k\frac{\partial}{\partial P_1}+(P_2-\overline{P_2})_k\frac{\partial}{\partial P_2}\right.$$
$$\left.+\cdots+(P_n-\overline{P_n})_k\frac{\partial}{\partial P_n}\right]^2\text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n}). \tag{10}$$

Expanding (10), we have

$$\overline{G_d}-\bar{G}\approx\frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2}{\partial P_i^2}\text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n})\cdot\frac{1}{m}\sum_{k=1}^{m}(P_i-\overline{P_i})_k^2$$
$$+\frac{1}{2}\sum_{\substack{i=1\\ j=1\\ n\neq j}}^{n}\frac{\partial^2}{\partial P_i\,\partial P_j}\text{map}(\overline{P_1},\overline{P_2},\ldots,\overline{P_n})$$
$$\cdot\frac{1}{m}\sum_{k=1}^{m}(P_i-\overline{P_i})_k(P_j-\overline{P_j})_k. \tag{11}$$

Two required conditions for scale invariance discussed before are still valid for Equation (11). If the parameters are homogeneous, then $P_i - \overline{P_i}$ is zero, thus the scale invariance holds. If the map is linear, the second-order derivatives of the map will be zero, and for this linear map, the scale invariance holds. If the map is weakly nonlinear, or the parameters are mildly inhomogeneous over the grid, a quasi-scale-invariant relationship may still be found because, under such conditions, the right hand side of Equation (11) will be small. For nonlinear maps, the correlation between parameters might be important in determining the effects of spatial heterogeneity (the second term in (11)). Based on current observational ability and measurement accuracy, we may consider that, if the error due to using a lumped model is less than 10%, the estimation error is acceptable.

If the map is not scale invariant, Equation (11) could still provide a method to parameterize the grid-scale output from a map. In order to estimate the grid-scale output, the lumped output should be modified by the map parameter heterogeneity. For a given map, we can obtain derivatives of the map with respect to its parameters. If we are able to parameterize the variances and covariances of parameters by their corresponding grid-scale values, then Equation (11) can be used to estimate the grid-scale map response by taking into account the spatial heterogeneity of parameters.

4. Applications

Equation (11) provides a systematic and general approach to examining scale-invariant properties of different maps. Here, we demonstrate the utility and effectiveness of Equation (11) to determine scale invariant characteristics of several commonly used land surface parameterizations.

4.1. Surface Infrared Radiation

A widely used model, based on the Stefan–Boltzmann law and modified for a non-black body, for surface infrared radiation, I, is written as follows

$$I = \varepsilon_e \sigma T_g^4, \tag{12}$$

where ε_e is surface emissivity, σ is the Stefan–Boltzmann constant and T_g is the canopy/soil combined temperature. For a given surface type, the surface emissivity depends primarily on moisture content. Soil moisture content and canopy/soil combined temperature depend on a number of land surface and atmospheric parameters and variables that exhibit natural spatial heterogeneity. Thus, the spatial distribution of surface emissivity and canopy/soil combined temperature will be heterogeneous. The surface infrared radiation map is a product of two heterogeneous model parameters as given in (12). Substituting this map into (11), we get

$$\begin{aligned}\overline{I_d} - \bar{I} \;=\; & 6\overline{\varepsilon_e}\sigma\overline{T_g}^2 \frac{1}{m}\sum_{k=1}^{m}[(T_g)_k - \overline{T_g}]^2 \\ & +4\sigma\overline{T_g}^3 \frac{1}{m}\sum_{k=1}^{m}[(\varepsilon_e)_k - \overline{\varepsilon_e}] \cdot [(T_g)_k - \overline{T_g}]. \end{aligned} \tag{13}$$

The relative difference can be expressed as

$$\frac{\overline{I_d} - \bar{I}}{\bar{I}} = \frac{6}{m}\sum_{k=1}^{m}\left[\frac{(T_g)_k - \overline{T_g}}{\overline{T_g}}\right]^2 + \frac{4}{m}\sum_{k=1}^{m}\left[\frac{(\varepsilon_e)_k - \overline{\varepsilon_e}}{\overline{\varepsilon_e}}\right] \cdot \left[\frac{(T_g)_k - \overline{T_g}}{\overline{T_g}}\right]. \tag{14}$$

Compared to mean values of canopy/soil combined temperature and surface emissivity, the difference produced by the heterogeneity will be very small. For example, the numerator of the first term on the right hand side will be on the order of a few kelvins whereas the denominator will be in excess of 280 K. Thus the difference between the aggregated output from a distributed surface infrared radiation parameterization and the lumped output from the lumped infrared radiation parameterization will be small. This suggests that surface infrared radiation parameterization may be quasi-scale-invariant.

4.2. Reflected solar radiation

The reflected solar radiation can be expressed as

$$R = \alpha S_{\otimes}, \tag{15}$$

where α is surface albedo and $S_{\otimes}$ is downwelling solar radiation at the land surface. The solar radiation at the surface will be affected by conditions in the atmosphere. For land surface modelling, however, it is generally assumed that the solar radiation at the surface is known and homogeneous over the grid. Thus, the map of reflected solar radiation is linear to the only parameter – surface albedo. From Equation (11), the difference between the aggregated output from a distributed reflected solar radiation parameterization and the lumped output from the lumped reflected solar radiation parameterization is zero. Consequently, we can argue that the reflected solar radiation parameterization is scale invariant. Similar results are also reported from the analysis of numerical experiments (e.g., Bonan et al., 1993).

We must emphasize here that Equation (15) is perhaps one of the simplest parameterizations for reflected solar radiation and it does not include many complicating factors, for example, the nonlinearity of albedo with topography and spectral dependence of albedo. However, over a large area of a GCM grid, it can be argued that the reflected radiation should be more or less linear, so that the grid-cell average reflected solar radiation will be approximately equal to the average of the subgrid aggregated output. Within a mountainous area, however, depending on the albedo and details of the topography (i.e., slope and aspect effects), there can be a significant difference, due to the different effects of topography at the subgrid versus the average effects of the topography at the grid level. Another interesting example may be seen in the marginal ice zone where the parameterization of the reflected solar radiation is complicated by the high reflectance of snow (up to 90%) and low albedo of water, and the reflection by clouds of upward (reflected) solar radiation. Thus, the interaction of the cloud and the surface might lead to the difference between the lumped and distributed model estimation of the grid level reflected solar radiation (Stossel and Claussen, 1993; and Grotzner et al., 1996). In such cases, Equation (15) needs to be refined to include the dependence of albedo on topography, or snow, and then Equation (11) should be used to quantify the difference between the aggregated output from a distributed reflected solar radiation parameterization and the lumped output from a grid-level input.

To illustrate the adequacy of our proposed method, let us consider another simple case. Let us assume that albedo varies with cloud cover, and solar radiation at the reference level is reduced by cloud over a grid block. Let c_f be the fraction of cloud cover over a grid block, then the parameterization of the reflected solar radiation can be expressed as

$$R = \alpha(c_f) S_{\otimes}(c_f). \tag{16}$$

Then from (11), the difference between the distributed and lumped approaches can be expressed as

$$\begin{aligned} \overline{R_d} - \bar{R} \;=\; & \left[S_{\otimes}(\overline{c_f}) \frac{\partial^2 \alpha(\overline{c_f})}{\partial c_f^2} + 2 \frac{\partial \alpha(\overline{c_f})}{\partial c_f} \frac{\partial S_{\otimes}(\overline{c_f})}{\partial c_f} + \alpha(\overline{c_f}) \frac{\partial^2 S_{\otimes}(\overline{c_f})}{\partial c_f^2} \right] \\ & \times \frac{1}{m} \sum_{k=1}^{m} [(c_f)_k - \overline{c_f}]^2. \end{aligned} \tag{17}$$

The difference between the distributed and lumped reflected solar radiation, if we use the map in Equation (16), will usually not be zero but will be a function of the cloud cover, solar radiation, and albedo. This result is quite different from the earlier result inferred from using a map in Equation (15). Analysis of these two maps would demonstrate that a different parameterization, and the assumptions related to the parameterization, could lead to different results for the same physical process. We must note, however, that our proposed approach is capable of distinguishing between the effects of different parameterizations for the same process.

4.3. Sensible heat flux

The most often used parameterization of sensible heat flux from the surface is the bulk transfer formula

$$H = \rho C_p C_h U (T_g - T_a), \tag{18}$$

where ρ is air density, C_p is specific heat of air at constant pressure, C_h is the transfer coefficient, U is wind velocity, T_g is canopy/soil combined temperature and T_a is air temperature. Here, ρ, U and T_a are known at the reference level. For a mesoscale or GCM grid, air density, wind velocity and air temperature at the first model level may be assumed to be homogeneous in space. This assumption may be justified by viewing the atmosphere as a spatial integrator, and is supported by the field experiment data analysis (Mahrt and Sun, 1995) and blending height concept (Wieringa, 1986; Mason, 1988; Claussen, 1995a, b). Mahrt and Sun (1995) found that the bulk aerodynamic formulation, based on spatially constant atmospheric variables and spatially varying surface conditions, closely approximates the area averaged heat flux. An implication of this result is that current modelling philosophy of using the bulk aerodynamic formulation with heterogeneous surface conditions and homogeneous first model level conditions over a model grid is an acceptable practice. Usually the air flow close to the surface is in equilibrium with the surface conditions. Consequently, due to the surface heterogeneity over some horizontal scales, the air flow over the heterogeneous surface and below the blending height does depend on the location of the surface. Thus, by taking the first model level height to be at least the blending height, we can assume the atmospheric conditions at the first model level height to be homogeneous in a grid block. Various values of blending height are used in the literature from 5 to 100 m (Mason, 1988; Claussen, 1991; von Salzen et al., 1996). However, Hipps et al. (1994) found that changes in the computed fluxes were less than 10% using either a blending height of 20 or 150 m, while von Salzen et al. (1996) found that the precise value of the blending height is of lesser importance in comparison to the parameterization of the exchange coefficient.

Based on the above discussion, one may argue that primarily, two parameters, C_h and T_g, in the sensible heat flux [map(C_h, T_g)] parameterization are influenced by surface heterogeneity. Since the sensible heat flux is linear in C_h and T_g respectively, the first term in Equation (11) is zero. The difference between the aggregated output from a distributed sensible heat flux parameterization and the lumped output from the lumped sensible heat flux parameterization is as follows

$$\overline{H_d} - \bar{H} = \rho C_p U \frac{1}{m} \sum_{k=1}^{m} [(C_h)_k - \overline{C_h}] \cdot [(T_g)_k - \overline{T_g}] \tag{19}$$

and the relative difference is:

$$\frac{\overline{H_d} - \bar{H}}{\bar{H}} = \frac{\frac{1}{m}\sum_{k=1}^{m}[(C_h)_k - \overline{C_h}] \cdot [(T_g)_k - \overline{T_g}]}{\overline{C_h}[\overline{T_g} - T_a]}. \tag{20}$$

In the above discussion, we have replaced the air temperature at the roughness height for heat with the surface canopy/soil combined temperature. Based on the similarity theory, the surface sensible flux is related to the air conditions at the roughness height for heat and the atmospheric conditions at the reference height. The difficulty with this approach is that the air temperature at the roughness height cannot be measured directly. For this reason, as Stewart et al. (1994), and Sun and Mahrt (1995) have argued, the temperature at the roughness height is replaced by the easily measured and modelled surface radiative temperature. This approach is widely used in the various land surface models and is also used in our analysis (Equation (18)). This substitution essentially implies that the transfer coefficient is now related to the difference between the surface temperature and the reference level temperature. As we argued above, the reference level temperature may be assumed to be homogeneous. A similar assumption was also made by Garratt and Prata (1996). An implication of this commonly used assumption and practice in numerical modelling of land surface processes is that the transfer coefficient becomes a function of the surface temperature. We note that such a practice of replacing roughness level temperature with surface radiative temperature would lead to some error. The formulation of Louis (1979), with modifications in Louis et al. (1982), states that the transfer coefficient is positively correlated with the air temperature and the roughness height for temperature while assuming the atmospheric temperature at the reference level is constant (Mahrt and Ek, 1984). Based on field experiment data analysis, Sun and Mahrt (1995) found that the exchange coefficient and the radiative surface temperature are positively correlated. Thus, if the heterogeneity of the heat transfer coefficient and the canopy/soil combined temperature is large, the difference between the aggregated output from a distributed sensible heat flux parameterization and the lumped output from a lumped sensible heat flux parameterization will be significant. In fact, the lumped sensible heat parameterization might significantly underestimate the grid-level sensible heat flux (Mahrt, 1987; Bonan et al., 1993; Grotzner et al., 1996). In summary, for a heterogeneous land surface, a positive correlation between surface temperature and heat transfer coefficient would introduce errors in the scaling up of sensible heat flux.

4.4. Latent heat flux

The commonly used latent heat flux parameterization is based on the bulk transfer scheme

$$E = \rho L_v C_q U(q_g - q_a), \tag{21}$$

where L_v is latent heat of evaporation, C_q is transfer coefficient for latent heat, q_g is surface soil specific humidity, q_a is the reference level specific humidity. Again, ρ, U, and q_a are known at the reference level, and are assumed to be homogeneous. Based on the discussion for sensible heat transfer coefficient above, we argue that C_q may also be related to surface temperature. We also note here that in most numerical modelling experiments, C_q and C_h are assumed to be equal. The latent heat flux map is similar to the sensible heat flux map and may be assumed to be affected primarily by two heterogeneous parameters. Similar to (19) and (20), the absolute and relative differences between the aggregated output from a distributed latent heat flux parameterization and the lumped output from the lumped latent heat flux parameterization are

$$\overline{E_d} - \bar{E} = \rho L_v U \frac{1}{m} \sum_{k=1}^{m} [(C_q)_k - \overline{C_q}] \cdot [(q_g)_k - \overline{q_g}], \tag{22}$$

$$\frac{\overline{E_d} - \bar{E}}{\bar{E}} = \frac{\frac{1}{m} \sum_{k=1}^{m} [(C_q)_k - \overline{C_q}] \cdot [(q_g)_k - \overline{q_g}]}{\overline{C_q}[\overline{q_g} - q_a]}. \tag{23}$$

In Equation (23), the relative error in the estimation of distributed and lumped latent heat flux will be dictated by the correlation between the transfer coefficient and surface specific humidity. There are two competing factors that control the magnitude of the surface specific humidity: surface temperature and wetness of soil. Higher surface temperature and wetter soil corresponds to larger surface specific humidity. However, high soil moisture usually corresponds to low surface temperature and low surface temperature usually leads to smaller transfer coefficient (by virtue of their usual occurrence in less unstable, or stable, conditions). Consequently, the correlation between heat transfer coefficient and surface specific humidity is unresolved. In fact, reported numerical results and analysis of observed data regarding the scaling of latent heat flux are also mixed. We speculate that the scaling of latent heat flux is dependent on the form of the parameterizations, as well as the state of the land and atmosphere system. For example, Wood (1994) reported that the lumped model can predict latent heat flux fairly well when the atmospheric demand is low but it fails to accurately predict the latent heat flux when the soil and vegetation conditions limit the actual evapotranspiration. This nonlinear dependence of latent heat flux upon the state of the land-atmosphere system complicates the assessment of scaling properties for latent heat flux parameterization. To resolve this issue, we need to first ascertain the nature of the correlation between heat transfer coefficient and surface specific humidity. However, one can make some simple arguments regarding the scaling properties of latent heat flux if we assume that the input solar radiation is constant, and the ground heat flux is small. Then, conservation of energy would dictate that the lumped latent heat flux parameterization should overestimate the grid-scale latent heat flux. In previous sections we have shown that the infrared radiation from the land surface and reflected solar radiation are at least quasi-scale-invariant, and the lumped sensible heat flux parameterization underestimates the grid-scale sensible heat flux. In fact, results of Dolman (1992) and Bonan et al. (1993) corroborate this inference regarding the overestimation of grid-scale latent heat flux. This implies that the heat transfer coefficient and surface specific humidity could be negatively correlated. Clearly there are several untested assumptions here that need to be validated using observed data before more definitive conclusions can be drawn about the scaling properties of the latent heat flux.

4.5. Comparison with results of recent experiments

There is a considerable debate over the importance of surface heterogeneity on the estimation of the surface fluxes. Several recent studies reported results of numerical experiments on the issues of spatial scaling of surface fluxes (Claussen, 1989; Claussen, 1990; Garratt et al., 1990; Pinty, 1991; Blyth et al., 1993; Bonan et al., 1993; Wood and Lakshmi, 1993; Li and Avissar, 1994; Grotzner et al., 1996). Claussen (1990), Pinty (1991), Blyth et al. (1993), Bonan et al. (1993), Li and Avissar (1994) and Grotzner et al. (1996) have shown that surface heterogeneity is important and should be taken into account in modelling studies, while Garratt et al. (1990) and Wood and Lakshmi (1993) found that the surface heterogeneity might not be significant for some purposes.

In an attempt to include the effects of subgrid variability into numerical models, Garratt et al. (1990) introduced random (in space) variations in roughness length and random (in space and time) surface perturbations of temperature and friction velocity into a mesoscale model and reported a measurable, but barely significant, response in the simulated flow dynamics of the lower atmosphere. Wood and Lakshmi (1993) also found that the latent heat flux and normalized difference vegetation index are not sensitive to surface heterogeneity.

On the other hand, Claussen (1989) found that micro- and mesoscale turbulent flux divergences are of the same orders of magnitude in the case of shallow grid boxes. Claussen (1990) found that the dispersion of scalar admixtures is particularly sensitive to variations of surface (or stomatal) resistance in a neutrally stratified, horizontally inhomogeneous atmospheric boundary layer. He has also shown that the grid-averaged transfer coefficient (of momentum and of scalar admixtures) generally overestimates the effective transfer coefficient due to the subgrid-scale correlation terms. Pinty (1991) has shown that the areally averaged fluxes are sensitive to specific mesoscale features within the domain based on a numerical simulation of HAPEX-MOBILHY experiment. Blyth et al. (1993) demonstrated that if part of the surface is wet, large errors in mean latent and sensible heat fluxes can result from using simple averages of the parameters. Bonan et al. (1993) and Li and Avissar (1994) found that the latent heat flux is sensitive to the variability of land characteristics. Grotzner et al. (1996) described a study of the impact of subgrid scale sea-ice inhomogeneities on the performance of the atmospheric general circulation model ECHAM3. They found that the sensible heat flux in the lumped model is always smaller than in a distributed model.

While the modelling results are quite mixed in regard to the importance of the surface heterogeneity, the analysis of field experiments has shown that this heterogeneity may not be as important as suggested by the numerical model results. Esbensen et al. (1981) have shown that monthly averaged wind speeds, temperatures and humidities can be used to estimate the monthly averaged sensible and latent heat fluxes from the bulk aerodynamic relations to within a relative error of about 10%, and the estimates of monthly averaged wind stress under the assumption of neutral stability are within about 5% of the monthly averaged non-neutral values. The analysis of the FIFE data set shows that the land-atmospheric models are scaleable (Sellers et al., 1992; Hall et al., 1992). Garratt and Prata (1996) have shown that there is a small error incurred when the average (temporal or spatial) of the upwelling longwave flux is computed using the mean of the surface-temperature measurements rather than using the mean of the fluxes corresponding to each surface-temperature measurement. Their results are based on the Hay site measurements in Australia and simple analytical reasoning. Below, we attempt to explain some of these observational and modelling results using our proposed framework.

Bonan et al. (1993) and Li and Avissar (1994) have shown numerically that infrared radiation from the surface is the least sensitive of a number of processes, to the land surface heterogeneity. This result is consistent with our analysis in Section 4.1. The main reason is that the deviations due to heterogeneity of surface emissivity and surface temperature from the means is much smaller than these mean values. For example, the soil emissivity can vary from 0.90 for wet soil to 0.98 for dry soil (Oke, 1978). Assuming the surface temperature variation is no more than 10 K over a grid, then the error due to using the lumped model is about 2% (Equation (14)). In Section 3, we have shown that homogeneous surface parameters of a map can lead to a scale invariant map. Thus relatively homogeneous surface temperature and surface emissivity fields can lead to a quasi-scale invariant infrared radiation parameterization.

The result from Bonan et al. (1993) on the reflected solar radiation is consistent with our analysis in Section 4.2. Since for larger areas the reflected solar radiation may be assumed to be linearly dependent on only one surface parameter (albedo), this linearity leads to a scale invariant reflected solar radiation parameterization.

The influence of surface heterogeneity on the sensible heat flux scaling has been found to be important by Bonan et al. (1993) and Li and Avissar (1994). This is also consistent with our analysis in Section 4.3. The interaction between the surface temperature and transfer coefficient explains the effect of surface heterogeneity on the scaling up of sensible heat flux.

Reported results on the scaling of latent heat flux are mixed. Wood and Lakshmi (1993) found that the latent heat flux is scaleable, while Bonan et al. (1993) and Li and Avissar (1994) found that the surface heterogeneity has a significant influence on the estimation of latent heat flux. Recently, Wood (1994) argued that the scaling of latent heat flux depends on the state of the system. Two land surface parameters (leaf area index LAI and soil wetness WSOIL) and an assumed spatial distribution (normal distribution) are common in the first three studies. Comparison of the coefficient of variation (c.v.) for a normal distribution does not indicate significant differences among these three studies. Wood and Lakshmi (1993) used c.v. = 0.25 for both LAI and WSOIL. Bonan et al. (1993) used 0.31 (1.8/5.9) for LAI and 0.17 (0.11/0.65) for WSOIL. Li and Avissar (1994) used c.v. = 0.25 (0.125/0.5) and 0.60 (0.3/0.5) for both LAI and WSOIL. This suggests that, to account for the effects of land surface heterogeneity, we need to consider other characteristics (e.g., higher order moments) of the probability density function. In fact, both Bonan et al. (1993) and Li and Avissar (1994) found that a skewed distribution resulted in much larger differences between the aggregated flux and the lumped flux. In summary, the nature of spatial scaling of latent heat flux in the numerical exercises appears to be an unresolved problem, since there are not enough data to support an assumed specific distribution for any land surface parameter. In addition, there are complications related to the state dependent nature of latent heat flux.

Our analysis on the the emitted infrared radiation from the surface (Section 4.1) and on the reflected solar radiation from the surface (Section 4.2) is consistent with the results from the analysis of the FIFE data by Sellers et al. (1992) and Hall et al. (1992). In contrast to our findings, Sellers et al. (1992) and Hall et al. (1992) reported that the sensible and latent heat fluxes are scaleable for FIFE. This difference between the findings from the analysis of the FIFE experiment data and our results may be explained by the relative homogeneity of the FIFE experimental site. This site is a 15×15 km area of tall prairie grass in central Kansas with a terrain of gently rolling hills (Sellers et al., 1992). In comparison with a typical GCM grid block (300×300 km), the FIFE experiment site is much more homogeneous. As we have shown in Section 3, relative homogeneity of parameters can lead to scale invariance, irrespective of the details of the parameterization. This may explain the scaling results derived from the analysis of FIFE data.

5. Concluding Remarks

An analytical approach for evaluating scale invariant properties of land surface parameterizations is presented. At least two conditions under which scale invariance holds are derived from this analytical approach. It is shown that a land surface parameterization can be scale invariant if the land surface is homogeneous, or the land surface parameterization is linear. For commonly encountered heterogeneous land surfaces and nonlinear land surface parameterizations, these two conditions would be difficult to meet. Consequently, an exact scale invariant condition would be difficult to satisfy for land surface modelling.

Preliminary applications show that this analytical approach can support results of several field and numerical experiments related to effects of land surface heterogeneity on the surface fluxes. The emitted infrared radiation from the surface and reflected solar radiation parameterizations are found to be relatively insensitive to land surface heterogeneity. Sensible and latent heat fluxes are shown to be sensitive to the land surface heterogeneity because of the correlation of the transfer coefficient with the surface temperature and surface humidity. These results should be further validated using field data at different spatial scales. Assumptions related to different parameterizations for the same process could potentially lead to different conclusions regarding the influence of spatial heterogeneity. Our proposed analytical approach, however, is capable of identifying the role of different parameterizations in estimating the influence of spatial heterogeneity.

Our proposed approach is simple, but it promises to provide essentially similar results obtained from most involved numerical experiments and analyses of extensive large-scale field experimental data. We must emphasize, however, that to keep the analytical approach tractable, we have made at least two major assumptions, (i) neglect of higher order terms that translates to neglect of higher order statistical moments, and (ii) ignoring the contributions of interactions at the subgrid level associated with lateral advection. A primary motivation for these assumptions is to ensure the proposed approach is tractable so that valuable insight may be gained by using commonly encountered, but simple, land surface parameterizations.

To extend the analytical approach, it will be necessary to include third- and higher-order terms in Equation (8). For example, to account for the effects of skewness in the probability density function of a parameter, we would need to include the third-order terms in Equation (8). With our current state of knowledge about land surface parameters and their interdependence, we feel more empiricism needs to be introduced if we are to include higher-order terms.

Another caveat we must acknowledge here is that we have used relatively simple application examples from the literature to demonstrate the adequacy of our proposed approach. In cases where these application examples are not appropriate, we need to use different maps to account for the effects of land surface heterogeneity. For example, our latent heat flux parameterization does not include effects of vegetation and heterogeneous distributions of soil moisture due to topography. With significant heterogeneity in topography, there can be appreciable redistribution of soil moisture such that the valley bottoms would evaporate at nearly the potential rate, whereas evaporation would be very low elsewhere. In such cases, a more detailed latent heat flux map must be used to characterize the effects of heterogeneity. Nevertheless, our proposed approach would be applicable to estimating aggregation errors by such detailed maps as well.

The proposed approach can also provide a systematic methodology to parameterize the effects of land surface heterogeneity and to design remote sensing algorithms. For the estimation of the grid-level response, the lumped response should be modified by the variance term and covariance term. Thus, a new representation of land surface heterogeneity may be achieved by parameterizing the variance and covariance terms with grid-scale mean values of parameters. Results from a land surface heterogeneity parameterization using the proposed approach, and its application in remote sensing algorithm design, will be reported in the future.

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