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A REMOTE-SENSING BASED TECHNIQUE TO ACCOUNT FOR SUB-GRID SCALE VARIABILITY OF LAND SURFACE PROPERTIES

William L. Crosson[1] and Charles A. Laymon

Institute for Global Change Research and Education[2]
Huntsville, Alabama

1. INTRODUCTION

One of the current challenges in weather and climate studies is to develop a better understanding of the surface-atmosphere interactions that play an important role in the representation of hydrologic processes within atmospheric models, and the spatial and temporal scales at which these processes need to be modeled. Development of better representations of land surface processes in coupled surface-atmosphere models should lead to improved understanding of land-atmosphere interactions from mesoscale circulations created by surface vegetation discontinuities up to climate change processes associated with changes in natural ecosystems.

The natural heterogeneity of land surfaces at basically all spatial scales poses serious difficulties for atmospheric and climate modelers. A single grid cell of an atmospheric model, having dimensions of tens to hundreds of kilometers, often contains a mixture of diverse land types such as forest, agricultural and open water surfaces. This condition has led many researchers to attempt to develop physically realistic yet computationally efficient techniques to account for this variability.

The objective of this paper is to present a method, transferable to a multitude of spatial and temporal domains, for use of high-resolution remote sensing measurements to account for spatial variability of surface properties within a grid cell of a coupled land-atmosphere model. Candidate surface properties include Leaf Area Index (LAI), albedo, surface temperature, precipitation, soil moisture and other quantities that may be observed or derived from remote sensors. We present an example in which LAI distributions for various landcover classes are estimated from the Normalized Difference Vegetation Index (NDVI). This technique provides a means by which high-resolution surface information may be simulated given information about the basic surface state obtained from low-resolution satellite imagery or surface/remote sensing data assimilation. The resulting statistical representation of variability is appropriate for land surface model applications in which surface processes are aggregated up to scales suitable for incorporation into atmospheric models.

The following observations and assumptions have guided the development of our methodology:

- The representation of surface energy fluxes in land surface models is based on flux-gradient relationships which are valid only for a homogeneous 'patch' within which surface properties are uniform.
- Atmospheric model grid cells cannot be considered truly homogeneous, and thus the physical equations used to diagnose fluxes are not strictly valid for grid-scale fluxes. The relationships between surface properties (temperature, moisture, roughness) and processes (energy fluxes) at these scales are poorly understood.
- Many of the relationships between surface properties and processes are non-linear to some extent, so that use of a mean value to represent the surface state for a model grid area of hundreds of square kilometers or larger is inappropriate in many cases. This has been demonstrated by Wetzel and Chang (1988), who examined the soil moisture-evapotranspiration relationship, and by Bonan et al. (1993) who found that surface fluxes are strongly influenced by sub-grid scale variability of LAI, stomatal resistance and soil moisture. The degree of non-linearity between various surface properties and processes is currently being examined by many

[1] *Corresponding author address*: William L. Crosson, NASA/ES44, Marshall Space Flight Center, Huntsville, AL 35812; Email: bill.crosson@msfc.nasa.gov

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investigators. Hall et al. (1992) examined scale dependence of remotely-sensed surface parameters using data from FIFE (First ISLSCP (International Satellite Land Surface Climatology Project) Field Experiment) within the SiB model (Sellers et al., 1986). In their analysis, remotely-sensed surface temperature and vegetation index at 120 m resolution were aggregated up to a model grid of 1 km. Their results indicate that scaling had an insignificant impact on their vegetation index and a moderate impact on surface temperature. However, the universal applicability of these results are unclear because the FIFE region is relatively homogeneous and because the aggregation was over less than an order of magnitude in length.

- Due to fundamental differences in surface biophysical properties (roughness, LAI, etc.) between different landscape elements (e.g. bare vs. vegetated surfaces; water vs. land) and the non-linear effects discussed above, it is problematic to combine in any meaningful way values of surface properties from the distinct patches to obtain 'effective' values--i.e., those which can be applied for the entire grid cell to accurately diagnose surface energy fluxes.

2. DATA SETS

The data used in this study were collected as part of the Convection and Precipitation/Electrification Experiment (CaPE), conducted in central Florida during the period 8 July through 18 August 1991 (Williams et al., 1992). The study domain for the analysis presented herein covers an area of approximately 20,000 km^2 in east central Florida, mostly south and west of Merritt Island. Detailed hydrometeorological analysis and modeling have been performed using the CaPE data to provide baseline estimates of surface energy and water fluxes (Laymon and Crosson, 1995). Remotely-sensed data from SPOT and other platforms, as well as landcover classification imagery were utilized in this project. These data have been used together to develop our method for characterizing sub-grid scale variability of surface properties, in this case LAI.

2.1 *Landcover Classification*

Landcover data for the state of Florida were obtained from the Florida Game and Freshwater Fish Commission. The landcover classification was performed using data from Landsat-TM at 30 m resolution. Reduced resolution (90 m) data were used in this study because the 30 m product was not available for the entire study area. Twenty-two landcover types were identified in this classification. For modeling purposes, this was generalized to ten basic land types similar to those used in the Biosphere-Atmosphere Transfer Scheme (BATS; see Dickinson et al., 1986) and the Marshall Land Surface Processes Model (Laymon and Crosson, 1995). Table 1 lists the land classes and the percent coverage of each within the study area.

Table 1. Descriptive statistics on NDVI and LAI for each of the landcover classes in the CaPE study area.

LC class	Description	% coverage	NDVI Mode	NDVI 99%	LAI Mean	LAI Max	Coefficient a	Coefficient b
1	Short grass	25.1	0.51	0.62	2	4	0.080	6.301
2	Evergreen shrub	20.9	0.51	0.63	3	5	0.342	4.257
3	Deciduous shrub	1.3	0.56	0.64	3	5	0.084	6.385
4	Evergreen needleleaf tree	8.0	0.57	0.65	5	7	0.455	4.206
5	Mixed woodland	0.5	0.60	0.66	5	7	0.173	5.608
6	Deciduous broadleaf tree	12.7	0.60	0.67	5	7	0.280	4.807
7	Evergreen broadleaf tree	2.2	0.55	0.65	5	7	0.786	3.365
8	Swamp/Marsh	8.3	0.43	0.61	2	4	0.382	3.851
9	Aquatic	9.6	0.00	0.46	0	0	N/A	N/A
10	Barren	11.4	0.00	0.62	0	0	N/A	N/A

2.2 *SPOT NDVI Data*

NDVI values at 20 m resolution have been obtained using data from three SPOT (Systeme pour l'Observation de la Terre) satellite overpasses during the study period. Results are presented here for the most cloud-free of these images, 12:08 LDT on 9 July, 1991. NDVI was calculated from SPOT HRV-2 channels 2 and 3, which have bandpass wavelengths of 0.61-0.68 μm and 0.79-0.89 μm, respectively. Cloud filtering, based on threshold values in each of the three spectral bands, was applied to eliminate cloud pixels from the analysis.

The probability density functions (PDFs) of NDVI have been estimated by calculating histograms for each of the ten landcover types within the study area. This analysis was conducted in a Geographic Information System (GIS) by overlaying the NDVI and landcover images, and segregating the NDVI pixels based on the associated landcover class. The NDVI histogram for landcover type 1 (short grass) using coincident SPOT and landcover imagery for the study area is shown in Figure 1. This is the dominant landcover for the study area, occupying more than 25% of the region. The NDVI distribution is slightly positively skewed with a mean of 0.48, median of 0.50 and mode of 0.51.

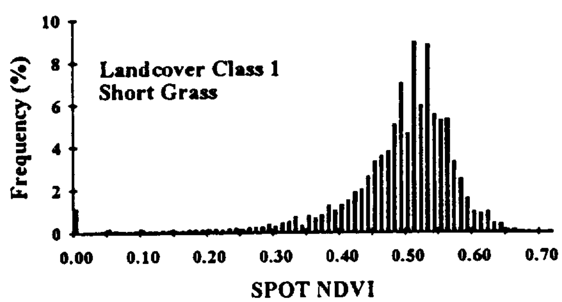

Figure 1. SPOT NDVI frequency histogram for pixels corresponding to landcover type short grass.

3. METHOD

3.1 *Existing Techniques for Representing Sub-Grid Scale Heterogeneity*

There are currently two basic approaches for parameterizing sub-grid scale variability of surface characteristics. The first paradigm ('mosaic' method) treats the surface within a model grid cell as a patchwork of different land types, each patch being homogeneous with respect to a set of defined surface parameters (e.g., Avissar and Pielke, 1989). A second paradigm uses statistical distributions (represented by PDFs) to quantify land surface variability. This 'statistical/dynamical' approach has been applied to various surface properties: soil moisture (Entekhabi and Eagleson, 1989); topography and soils (Famiglietti and Wood, 1991); LAI and stomatal resistance (Bonan et al., 1993). Avissar (1991) and Li and Avissar (1994) combined the two approaches by considering the PDFs of surface characteristics within each of a set of surface patches. These studies have shown that representation of sub-grid scale variations in surface properties significantly alters model-estimated energy fluxes.

3.2 *A New Remote Sensing-Based Technique*

The two paradigms mentioned above have inherent strengths but are incomplete approaches in and of themselves. The mosaic approach is an adequate first-order attempt to account for sub-grid scale variability, but does not consider within-patch variability due to fine spatial scale, short time scale processes such as non-uniform rainfall distribution and the resulting soil moisture distribution. In some cases it may be the spatial variability of evaporation, and not its absolute magnitude, which influences mesoscale convective precipitation, due to the resulting differential heating of wet and dry regions. Applications of the statistical/dynamical approach have relied on hypothetical statistical distributions of surface properties. Our technique is a modified version of the statistical/dynamical method, differing from previous efforts in its use of high-resolution remote observations instead of assumed probability distributions.

In this method, PDFs of remotely-sensed parameters are used to represent spatial heterogeneity of corresponding surface properties within each of a set of landcover patches. We are using landcover type to define the surface patches; in other applications the land surface may be partitioned according to topographic index, soils, or other variables, or a combination of variables. The connection between the remotely-sensed quantity may be direct, as in the case of surface albedo or temperature, or indirect, in the case of LAI. The proposed technique provides a mechanism by which statistical properties of small-scale surface heterogeneity, observed periodically with high-resolution remote sensors, can be utilized to simulate the nature of the surface properties (and associated processes) at the scale at which physical principles are applicable. In the present investigation, variability of only one surface property is being modeled. In practice, multiple variables may be varied, but the number of model runs increases dramatically. The basic steps involved in applying this method using a land surface model are as follows:

(1) For each land surface patch, the PDF is estimated for the controlling surface variable based on remotely-sensed data. For most variables, such as surface temperature and albedo, the distribution is with respect to a temporally changing mean value, while for others,

such as LAI, distributions need only be defined seasonally.

(2) A land surface process model is run for each of the landcover patches. The PDF for the controlling surface variable for each patch is divided into a number of intervals.

(3) For each land surface patch, the model is run once for each PDF interval, with the value of the controlling variable given by the midpoint value of the interval.

(4) The model outputs for a given surface patch within the grid cell are calculated by probability-weighting the outputs obtained for each PDF interval.

(5) The grid cell mean flux is obtained by weighting the patch means obtained in (4) according to the fraction of the grid cell occupied by the particular patch.

3.3 *Application - Leaf Area Index Derived from NDVI*

In this study, the statistical distribution of NDVI for each of the landcover classes is used to represent the variability of LAI. In order to estimate the distribution of LAI from the observed PDF of NDVI for each landcover class, we must assume a functional form of the relationship between the quantities. Previous studies have used linear (Curran et al., 1992) or exponential (Nemani and Running, 1989) relationships. The latter is preferable due to decreasing sensitivity of NDVI at high LAI levels. Thus we assume the following functional form:

$$LAI = a \bullet e^{b \bullet NDVI} \quad (1)$$

The coefficients a,b are found by simultaneously solving (1) for two fixed points. To define these points, we use LAI and NDVI values representative of a typical or mean value, and a maximum value associated with a particular landcover type. Because no LAI measurements were made in CaPE, estimates of mean and maximum LAI (LAI_{mean}, LAI_{max}) have been set at levels similar to those used in BATS (Table 1).

Statistical properties of the NDVI distributions -- mean, median, mode, standard deviation, percentiles -- have been calculated from the histograms for each landcover class (Table 1). We use the mode and 99^{th} percentile of the NDVI distributions corresponding to mean and maximum LAI. The NDVI mode ($NDVI_{mode}$), is defined here as the midpoint of five contiguous histogram bins, each having width of .01, having the maximum aggregate frequency of occurrence. The maximum value of NDVI ($NDVI_{max}$) is estimated using the 99^{th} percentile to avoid biasing due to a very small number of large values which may result from slight geolocation errors. The mode and maximum values are given in Table 1.

Having solved for the coefficients in (1), NDVI frequency distributions as illustrated in Figure 1 may be converted into LAI frequency distributions by applying (1) to values representing each NDVI histogram bin and calculating frequency of occurrence for a set of LAI values. The result for the short grass landcover class is shown in Figure 2, where the LAI bin width is 0.2. The LAI distribution peaks at 2.0 (LAI_{mean}) and the maximum value is 4.0 (LAI_{max}).

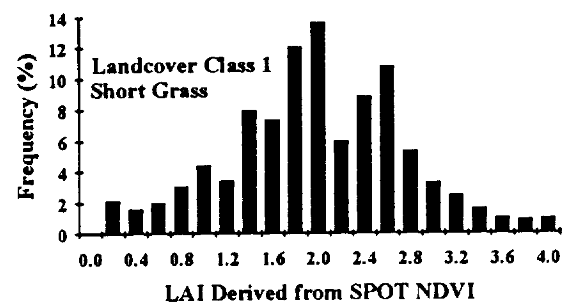

Figure 2. Frequency histogram of LAI for landcover type short grass, derived from NDVI using exponential relationship.

4. DISCUSSION

The set of frequency histograms for all landcover classes, as well as the spatial distribution of the classes within the study area, provides the necessary information to account for the spatial variability of surface properties (in this example, LAI) in the context of land surface process modeling. In applying this technique, every model grid cell is treated as a mosaic of patches. Sub-grid scale variability within each patch is incorporated by imposing probability distributions of the controlling surface properties.

This technique is well-suited for experiments designed to test model sensitivity to land surface parameterizations. The following issues may be addressed through a series of model simulations:

- Which surface variables exhibit the most scale-dependence or have strong non-linear influences on surface fluxes?

- In a coupled land-atmosphere model, which surface properties are the most important to represent at sub-grid scales, and how much detail is necessary to characterize them? The answer to this undoubtedly is a function of the variable and the climate regime.

- How can or should information from fine scales be aggregated up to model grid cell size?

5. CONCLUSIONS

A method has been presented for the representation of sub-grid scale variability of surface properties within a land surface processes model. The method uses remotely-sensed data to directly or indirectly estimate probability density functions (PDFs) of key surface variables. Application of this technique in a coupled land surface-atmosphere model requires only grid-scale values of the variables of interest, obtained from low-resolution satellite imagery or surface/remote sensing data assimilation. The PDFs of each controlling surface property are superimposed on the respective grid-scale values to simulate sub-grid scale heterogeneity. Sensitivity studies will be carried out to ascertain the relative importance of the heterogeneity of several variables, and the degree to which non-linear property-process interactions impact large-scale fluxes.

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