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Forest ecosystem processes at the watershed scale: basis for distributed simulation

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ABSTRACT

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A framework is described to compute and map forest evapotranspiration and net primary productivity over complex mountainous terrain. The methodology is based on the interface of geographic information processing and remote sensing with FOREST-BGC, a nonlinear deterministic model designed to simulate carbon, water and nitrogen cycles in a forest ecosystem. The model requires as input the geographic patterns of leaf area index (LAI), available soil water capacity (SWC) and microclimatic parameters over the landscape. These patterns are represented with the use of a template consisting of the set of hillslopes, stream channels and subwatersheds that completely define the landscape. A geo-referenced database containing digital elevation data, remotely sensed information and other environmental data are stratified by this template. We have found that the stratification of the surface data sets by a hillslope or watershed template produces landscape units with low internal variance of the important model parameters but high between unit variance. By producing templates at different levels of resolution, we have the ability to reorganize the model parameter set to different levels of surface generalization. The model is directly parameterized for each of these surface units which can then be simulated in parallel, providing the ability to expand the simulation to large regions.

INTRODUCTION

This paper introduces a method to expand point process ecologic models to landscape levels. We use an existing forest ecosystem process model, FOREST-BGC (Running and Coughlan, 1988), in conjunction with geographic information processing and remote sensing to spatially structure,

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parameterize and execute a simulation of forest evapotranspiration (ET) and net primary productivity (NPP) for watersheds in western Montana. our ultimate goal is to produce a methodology with which we may produce estimates of these and other ecologic and hydrologic flux rates and storage levels over a spectrum of scales ranging from the hillslope or tree stand that FOREST-BGC was initially developed to operate at and which can be directly sampled and validated in the field, through areas on the order of 10^4 km^2. This latter level is the scale of a global circulation model (GCM) grid cell. We have previously used remote sensing pixels of the Advanced Very High Resolution Radiometer (AVHRR) to organize FOREST-BGC model parameters (Running et al., 1989) for regional level simulations. While the AVHRR simulations were able to reveal large scale patterns of the ecosystem processes, the substantial landscape variation and information that exists below the resolution of these cells (1 km^2) in mountainous environments cannot be represented, and is therefore difficult to directly validate.

Extensive sensitivity analyses (Running, 1984) and experience with FOREST-BGC have shown the most important model parameters to be air temperature (T_a) and vapor pressure deficit (VPD), solar radiation (Q), leaf area index (LAI) and soil available water capacity (SWC). In mountainous terrain, these parameters form microenvironments that follow spatial patterns with well expressed regular and random components according to the local slope, exposure, landscape position and disturbance. In the water-limited Rocky Mountain ecosystems of western Montana, there is a strong topographic control of the radiation environment, forest structure and typical soils with more open canopies occupying sunlit southern-facing slopes and more closed canopies occupying shaded northern-facing slopes. Even when human or natural disturbance dominates the forest patterns, the radiation environment shows strong contrasts on the basis of exposure. We have therefore chosen hillslope facets to be a basic landscape unit for both the sampling and storage of the geographic information necessary to compute the values of the model parameters, and for distributed model execution.

The basic strategy that we follow is to develop efficient, automated techniques to partition a digital elevation model (DEM) of the landscape into different numbers of topographically defined units (in this case, hillslopes). Information from geographically registered remote sensing imagery, the DEM and digitized soil maps are used to derive the site-specific model parameters including the surface gradient, aspect, elevation, LAI and SWC. These parameters are then aggregated to the hillslope level using the topographic partition as a template.

We can flexibly define the detail and scale of the partition by controlling the degree of landscape dissection resolved on the DEM, and therefore, the number and size of the hillslopes. At each partition scale we simulate forest ET and NPP for each hillslope. The effects of aggregation can then be explored in terms of total watershed response and the spatial and temporal patterns that are modeled. We also attempt to estimate the variance and bias of the ET and NPP predictions that are produced by the aggregation process. Some caution must be exercised when surface information is aggregated into increasingly larger regions if the simulation models exhibit significant nonlinearities over the increasing ranges of the parameter values encountered. Under these circumstances, use of mean values of the parameter values may not yield mean values of the response variables. The range of parameter values relative to the model nonlinearity can be taken as a dominant concern in the choice of landscape partition strategy. When a model behaves linearly larger partition units can be used without significant bias. As the nonlinearity grows, however, smaller more homogeneous landscape units are required. Note that a model may behave linearly over certain parameter ranges, but very nonlinearly over other ranges encountered at different geographic scales, locations or at different times.

In the present paper, we present the theoretical principles guiding the aggregation procedure, and the remote sensing and geographic information processing methodology required for implementation. In particular, we show how we flexibly partition and parameterize a watershed into varying numbers of basic landscape units to act as templates to register and aggregate all model parameters estimated from digital maps, remotely sensed data and digital terrain data. A comparison is made between the efficiency of using the landscape units (hillslopes) defined from the digital terrain data and the use of a more conventional grid template. We briefly describe FOREST-BGC and its sensitivity to the required parameters along with observed parameter variability as estimated by the remote sensing and geographic information processing. Within this context, we explore the effectiveness of different partition scales in producing a set of landscape units with low within unit variance of the model parameters compared to the between units variance. The entire process is illustrated with the parameterization and simulation of ET and NPP in the North Fork of Elk Creek, an experimental watershed in western Montana. The simulations are run at three levels of spatial complexity, corresponding to a progression of surface segmentations into increasing numbers of hillslopes.

In this paper the terms hillslope and landscape unit are used interchangeably, although we emphasize that the size and complexity of any hillslope is dependent on the scale of landscape representation chosen (this is further discussed, below) and we could also replace hillslopes with watersheds or other landscape features that would efficiently stratify the important model parameters.

MODEL DESCRIPTION

FOREST-BGC is an ecosystem simulation model that was designed to reproduce the key processes involved in the carbon, water and nitrogen cycles of forests. It is a compromise between the canopy physics of detailed biophysical models and the more general, functional or statistical approaches to the interactions of climate and vegetation that are used over regional scales. The model strives to retain the significant physical interactions between the external environment and forest ecosystems, while allowing an adequate parameterization with information derived from remote sensing and geographic information systems. The model has been described in detail by Running and Coughlan (1988) and is discussed here just in sufficient detail to present our strategy for model extrapolation.

Required input data includes daily meteorological conditions for a base station and site-specific data for each surface unit, including topographic, soil and canopy information describing the topoclimatic environment, soil hydraulic and canopy structural and physiological conditions (Running and Coughlan, 1988). A semi-empirical model, MT-CLIM, extrapolates the base station climatic data according to elevation, aspect and gradient through the surrounding complex terrain (Running, Nemani and Hungerford, 1987). Using these and other derived parameters, FOREST-BGC calculates canopy interception and evaporation, transpiration, soil water outflow, canopy photosynthesis, growth and maintenance respiration, carbon allocation, litterfall and decomposition, and nitrogen uptake and mineralization of nitrogen. The hydrologic, photosynthetic and maintenance respiration terms use daily time steps, while the carbon and nitrogen processes use annual time steps.

FOREST-BGC routes water from precipitation into snowpack or soil water, less the canopy interception as computed from the leaf area index (LAI). Throughfall and snowmelt water move into the soil rooting zone compartment where it becomes available for root uptake. Leaf transpiration, calculated with a Penman–Monteith equation based on micrometeorologic data, leaf water potential (LWP) and LAI, drives the uptake and conductance of soil water as modified by physiologic conductance and soil water availability terms. Canopy photosynthesis is a function of the CO_2 diffusion gradient, a radiation and temperature controlled mesophyll CO_2 conductance, the canopy water vapor conductance, LAI and the daylength. Average canopy radiation is computed from Beer's Law for extinction of incident shortwave radiation through the canopy, and all physiologic parameters are assigned as species-specific. In the present paper, we restrict our interest to evapotranspiration and photosynthesis and do not produce carbon and nitrogen cycling information.

FOREST-BGC was designed and has been operated as a point, or stand-level simulation model. As such, the model parameters have been implicitly considered to have no variation for a given simulation. However, the present use of the model seeks to parameterize and execute the simulations over extensive areas characterized by strong spatial variability of the important model parameters. Therefore, when the spatially continuous parameter fields are aggregated into a set of discrete landscape units for simulation, variance is introduced into the model parameters. If we represent the landscape units with the mean values of the parameters, then for any given point within the landscape unit, the recorded parameters are in error and the modeled results will be in error by an amount proportional to the deviation of the point's true parameter values relative to the landscape unit mean values, and the model's sensitivity to these deviations.

If the model behaved linearly at all times, the sum of these errors would approach zero and use of mean parameter values would give unbiased flux estimates. Because FOREST-BGC can be highly nonlinear under certain conditions the individual point deviations may not be self-cancelling and the mean simulation deviation may be non-zero. This would add a bias to the modeled results if no account of the landscape unit internal variance were taken, which can become significant. Note that linear models, such as those based on simple linear or multiple linear regression will not show this form of bias. While this makes the linear models simpler to parameterize and operate, we feel that since the dominant physical processes of energy and mass exchange in the hydroecologic systems we are modeling are characterized by strong nonlinearities, models that are based on empirical linear relationships between observed ecosystem variables (such as precipitation, temperature and productivity) are limited in their abilities to reproduce natural system behaviour beyond the range of the original observations. Unfortunately, with the more realistic nonlinear process models comes significantly greater difficulty in parameterization. This is addressed in the next section.

THEORETICAL BASIS FOR SPATIAL AGGREGATION

As indicated above, the manner in which continuous geographic information fields are aggregated into discrete landscape units may have significant impacts on both the parameterization and results of hydroecologic simulation models. This impact is largely dependent on the variance of the parameter values within the landscape units and the degree of model nonlinearity over the parameter range. Figure 1 illustrates a response curve of annual ET to changes in LAI for fixed climatic conditions of a water-limited ecosystem in western Montana. The simulations for this curve were for a

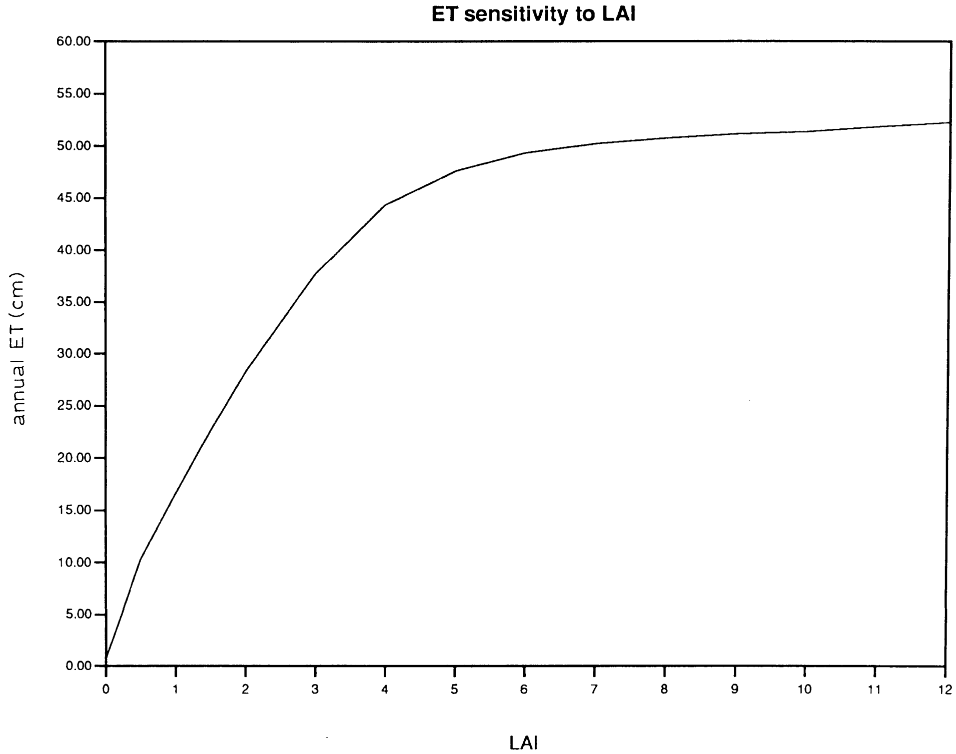


Fig. 1. Response curve of annual ET with respect to LAI for a south facing slope in western Montana. Hillslope gradient is 10° and the SWC is 15.0 cm.

south-facing slope with an SWC of 15.0 cm. If we consider a hypothetical hillslope with an LAI range from 1 to 3, we can see that the modeled response is nearly linear. In this case, entering a mean LAI value of 2 will yield a ET close to the average ET response. On another hillslope with LAI evenly distributed over a range from 2 to 8, it can be seen that the mean LAI 5.0 will significantly overestimate the average ET response. This type of LAI range may occur as a result of human or natural disturbance, or may occur in an undisturbed ecosystem in our study area when moving over a ridge from a north-facing slope with a closed conifer canopy to a south-facing slope with an open canopy. Similar arguments can be made regarding the variability of solar radiation over these slopes.

The magnitude of the bias relative to the expected value of ET over the entire hillslope is due to the nonlinearity of the response within the particular range of the model parameter (LAI) for each hillslope. Therefore, segmenting the landscapes into units over which the range of the important model parameters are small or the model behaves approximately linearly can be a guiding partitioning strategy.

The above considerations can be formalized with the methods of classical error or variance propagation (e.g. Meyer, 1975). Bresler and Dagan (1988a, b) and Dagan and Bresler (1988) considered the effect of spatial variability and uncertainty of parameters on aggregate crop yield for a single field. Their study demonstrated a methodology to estimate the mean and variance of the aggregate yield using a validated, deterministic point process model and a given parameter distribution function. Our study is similar to the extent that we are interested in the ability to simulate complex environmental processes over heterogeneous terrain by representing as much of the parameter distributions as possible with mean or representative values. However, we also have control over the landscape units actually used by constructing a partition process that will produce low internal heterogeneity of each unit while maintaining its hydrologic and ecologic functionality (e.g. hillslopes as runoff source areas). This gives us the ability to trade off the complexity with the number of individual simulations.

The procedure of expanding a point model to large areas may be represented by the integration of some function over a geographic parameter field. To do this we represent the environmental point process by a function, P, such that:

$$p(x) = p(\alpha_1, \alpha_2, \ldots, \alpha_n) \tag{1}$$

where the α_i are the model parameters specific to the location x; x may be a point or a patch that is considered to be homogeneous in the important model parameters, and we consider that a potentially large number of x comprise each discrete landscape unit (i.e. hillslope or field) that will be simulated. Within a raster-based GIS using high resolution remotely sensed imagery, these points or patches may be taken as the pixels. Each landscape unit is characterized by a multivariate density function, $f(\alpha_1, \alpha_2, \ldots, \alpha_n)$ of the model parameters produced by integrating the α_i over all x. If we consider $P(x)$ to be a spatially independent process (i.e. interaction with neighboring points is negligible) then the spatial pattern of the α_i is unimportant and the integration of $P(x)$ over all x is equivalent to integration over the density function of the α_i:

$$\int^{x} p(\alpha_1, \alpha_2, \ldots, \alpha_n)\, \mathrm{d}x = \int^{f} p(\alpha_1, \alpha_2, \ldots, \alpha_n) \times f(\alpha_1, \alpha_2, \ldots, \alpha_n)\, \mathrm{d}f \tag{2a}$$

where

$$\int^{f} (\ldots)\, \mathrm{d}f = \int^{\alpha_1}\int^{\alpha_2} \ldots \int^{\alpha_n} (\ldots)\, \mathrm{d}\alpha_1\, \mathrm{d}\alpha_2 \ldots \mathrm{d}\alpha_n \tag{2b}$$

Computationally (2b) becomes a summation over an n-dimensional table of joint parameter frequencies. It is apparent that a major effort would be involved in this computation and summation over the joint frequency distributions for all landscape units in a region, in addition to the sampling effort of actually specifying f for each unit. We would therefore like to simplify this portion of the integration by attempting to represent the effects of the full parameter distribution by a set of mean or representative values of the α_i. This approach is ensured to produce unbiased estimates only if p is sufficiently linear over the range of the α_i present in each subregion as illustrated above, and discussed by Bresler and Dagan (1988).

When it is not practical to produce landscape units satisfying this constraint, we need to consider the variance of the, point process through each spatial unit. If the α_i have sufficiently small variance in a given unit, then for each x:

$$P(x) = p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n) + \sum_{i=1} \frac{\partial p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n)}{\partial \bar{\alpha}_i}(\alpha_i - \bar{\alpha}_i)$$

$$+ \tfrac{1}{2} \sum_{i=1} \sum_{j=1} \frac{\partial^2 p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n)}{\partial \bar{\alpha}_i \partial \bar{\alpha}_j}(\alpha_i - \bar{\alpha}_i)(\alpha_j - \bar{\alpha}_j) + \ldots \tag{3}$$

This simply gives the result of the point process at a location x as a Taylor Series expansion about the mean values of the parameters. The first term in the right hand side of (3) gives the result of using the mean values of the model parameters over an area, while the next two terms add the deviations to that response at x induced by the deviation of each parameter from its mean value, and covariance of the parameters. If there were negligible variance of the parameters over the landscape unit relative to the sensitivity of the model, these latter two terms would tend to zero. Summing over all x gives the expectation of P:

$$E(P) = p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n) + \tfrac{1}{2} \sum_{i=1} \sigma_{\alpha_1}^2 \frac{\partial^2 p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n)}{\partial \bar{\alpha}_i^2}$$

$$+ \sum_{i=1} \sum_{j=1} \frac{\partial^2 p}{\partial \alpha_i \partial \alpha_j} \sigma_{\alpha_i \alpha_j} + \ldots \tag{4}$$

where $\sigma_{\alpha_i}^2$ is the variance of α_i and $\alpha_{\alpha_i} \sigma_{\alpha_j}$ is the covariance of α_i and α_j. In (4), no independent linear terms appear as the expected values of the $(\alpha_i - \bar{\alpha}_i)$ are zero, leaving only the nonlinear and cross-parameter terms. Therefore, if $p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n)$ is linear over the range of the α_i (all higher order derivatives are zero) or the variances and covariances are small:

$$E(P) = p(\bar{\alpha}_1, \bar{\alpha}_2, \ldots, \bar{\alpha}_n) \tag{5}$$

which gives us the computationally simplest result. One primary goal of the surface stratification methods is to outline spatial units for which (5) is

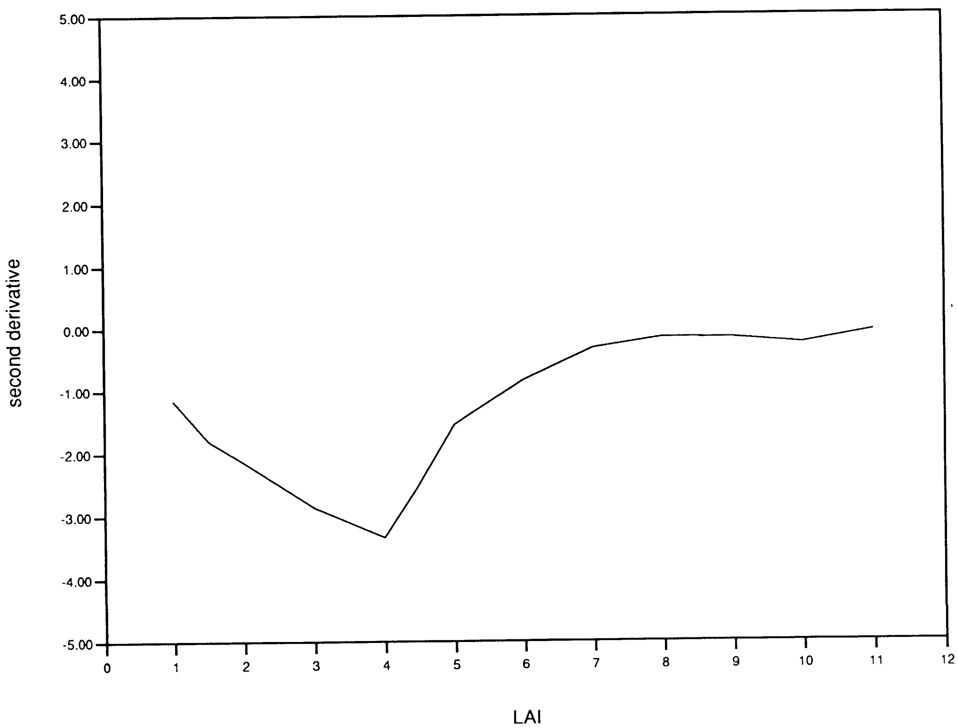


Fig. 2. Second derivative of ET with respect to LAI, for the curve in Fig. 1.

valid. Procedures to accomplish this goal are the main focus of this paper and we concentrate on outlining landscape units with low internal variance.

When this is not possible we can estimate the mean value of the point process model results for each landscape unit from knowledge of the means, and variance-covariance structure of the input parameters as in (4). These may be gained either from direct sampling, or by a priori or modeled knowledge of the terrain characteristics. In many cases direct sampling will not be possible for all significant model parameters, and so it is important to employ or develop tools to estimate the within unit patterns or variability by the latter methods. We also need to know the magnitudes of the second derivatives of the model output (i.e. ET or PSN) with respect to the model parameters in the neighborhood of the mean parameter values.

To illustrate the use of (4) we investigate the impact of variable LAI on annual ET, using the response curve in Fig. 1. The second derivatives of this curve, $\partial^2\text{ET}/\partial\text{LAI}^2$, over the range of LAI (Fig. 2) can be used to indicate those conditions under which significant bias in the estimation of the expected annual ET may occur using only the mean LAI in the computation. Given a mean LAI for a hillslope, $\partial^2\text{ET}/\partial\text{LAI}^2$ is read from Fig. 2, and with a given variance we can solve for the effects of variation in LAI on the mean ET depth as in the second term of (4). If a hillslope has a mean LAI of 2.0 and a variance of 1.0, the additional term is about -2.2 cm that must be taken away from the value of 28.2 cm ET (from Fig. 1). If a hillslope has a mean LAI of 4.0 and a variance of 2.0, the additional term is about -6.7 cm relative to the value of 44.3 cm ET if there were zero LAI variance.

The quantities contributed by variance of the other parameters must be added to these terms, along with the contributions due to covariance of parameters (the third term in equation 4). These additional terms may be positive or negative, so that the total bias may be augmented or dampened depending on the sign of the second derivatives and covariances. It should be noted that if the effects of a number of the parameter variances and model nonlinearity cannot be neglected, these additional expansion terms may require substantial additional computation. Therefore, emphasis must be placed on finding landscape regions over which most of these terms can be neglected.

In summary, in accordance with (1) and the preceding discussion, determination of the aggregate response of a region first requires a segmentation of the total area into landscape units with known or estimated f. At the minimum, we need to be able to determine the means, variances and covariances of the model parameters within each surface unit. It is preferable that each f have a sufficiently narrow parameter range (low values of the σ_i) within which the model behaves linearly. We would also like to avoid having to produce too many subunits to ensure that we are not performing numerous redundant parameterizations and simulations. In this latter case, use of the Taylor series approximations as given by (4) for the case of near-normal f, may allow us to avoid the integration of the model over the full joint parameter distribution.

GEOGRAPHIC INFORMATION PROCESSING

The preparation of the landscape template and estimation of the model parameters for each landscape unit involves a combination of digital terrain analysis, remote sensing, and geographic information processing. We are in the process of building an integrated software system to automate this data preprocessing and model parameterization stage, along with the actual model execution and output production. The basic structure of RHESSys (Regional Hydroecologic Simulation System) is shown in Fig. 3. A substantial portion of the computation and analysis is devoted to the processing and combination of the primary data files. The product of these steps are the fixed site information included in the cartridge file, holding the fixed

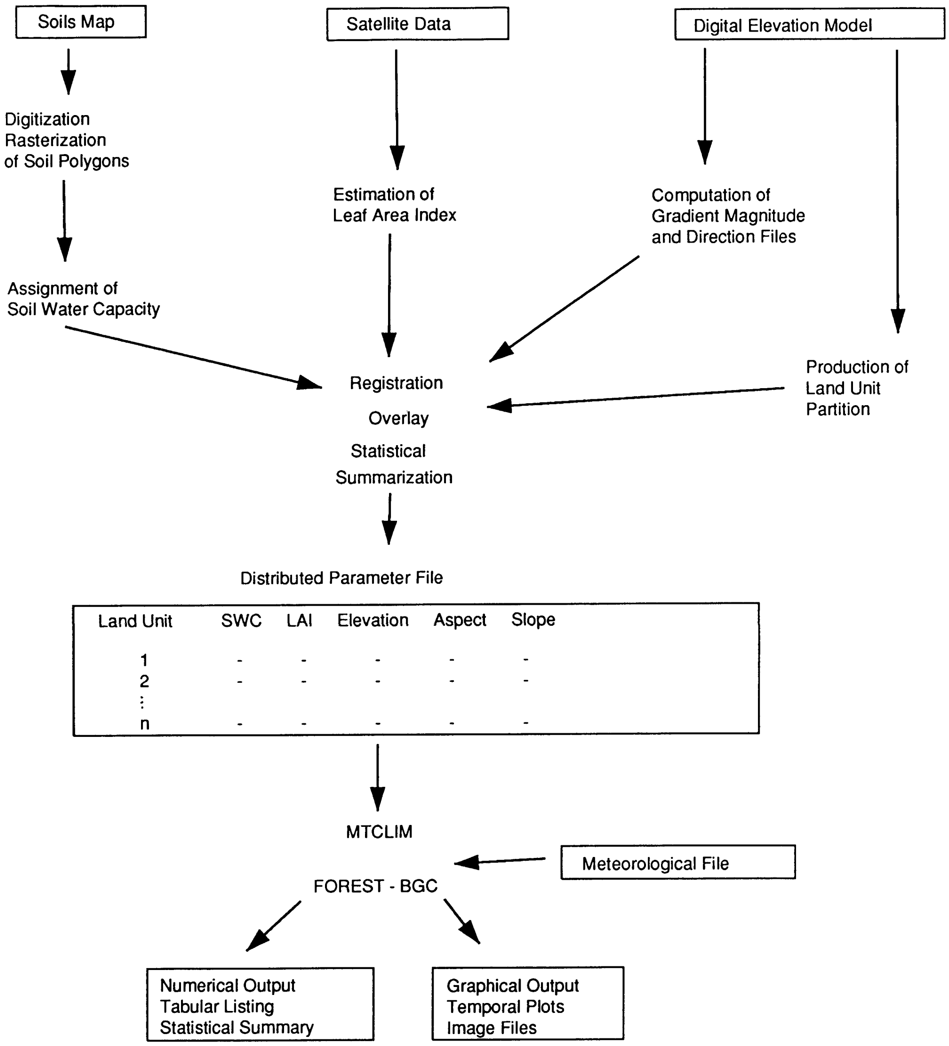


Fig. 3. Generalized flow chart RHESSYS, tracking information from primary map and image data sources, through the distributed parameterization and simulation scheme.

landscape parameters, which in combination with base station meteorological information are used to estimate all model parameters.

Each entry in the cartridge file represents a landscape unit as outlined by the digital terrain analysis. At this stage, the current cartridge file can be pulled out and another cartridge file inserted to model another representation of the landscape. Alternative representations can be hillslopes of different scales, subcatchments, watersheds, or any other partition, including a grid.

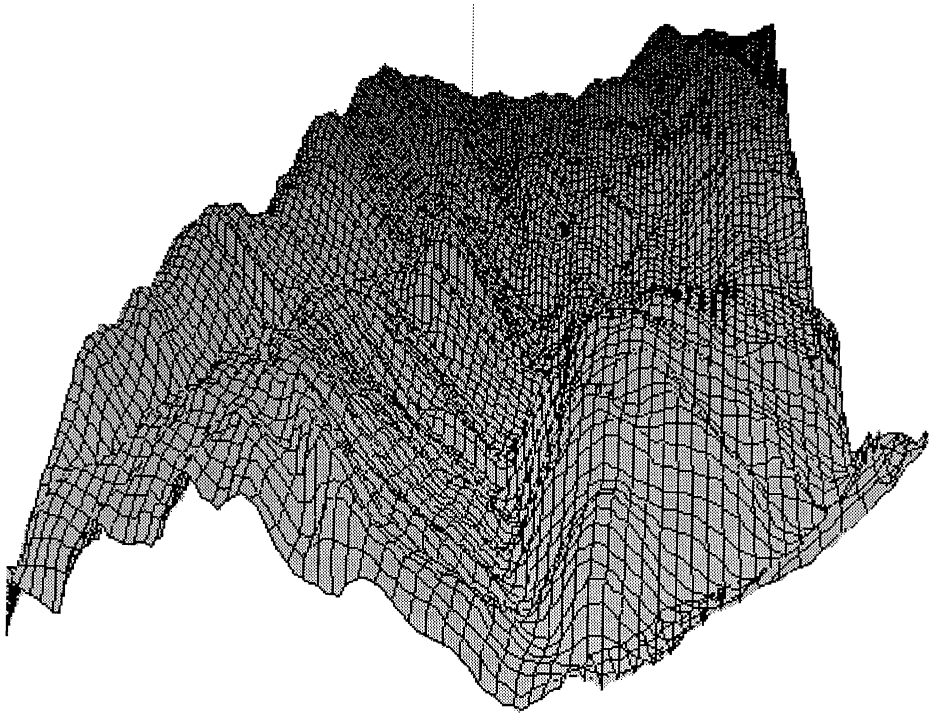


Fig. 4. Perspective view of the DEM containing the North Fork of Elk Creek.

Digital terrain analysis and surface partition

In our study sites of western Montana, the strong influence of topographically controlled microclimate on surface ecologic processes results in a geographic pattern of forest cover that closely follows the pattern of hillslope facets. A hillslope is defined here as the drainage area contributing flow to a stream link from one bank. A link is a stretch of stream channel, along which no tributaries enter. Therefore, a link is the simplest component of the channel network [see Abrahams (1984) for an excellent discussion of stream channel network structure]. We have selected the topographic partitions to act as templates to organize all other parameter images over the range of scales at which we operate the simulations. In the simplest case, the hillslopes show low environmental variation over their areas and we may summarize the hillslope information with a single vector of mean or representative model parameters.

Our study site is on the border of two USGS 30-m digital elevation models (DEM), which we had to mosaic and then extract a subwindow containing the test watershed (Fig. 4). Figure 5 shows a decomposition of the North Fork of Elk Creek, a 17 km^2 experimental watershed in western

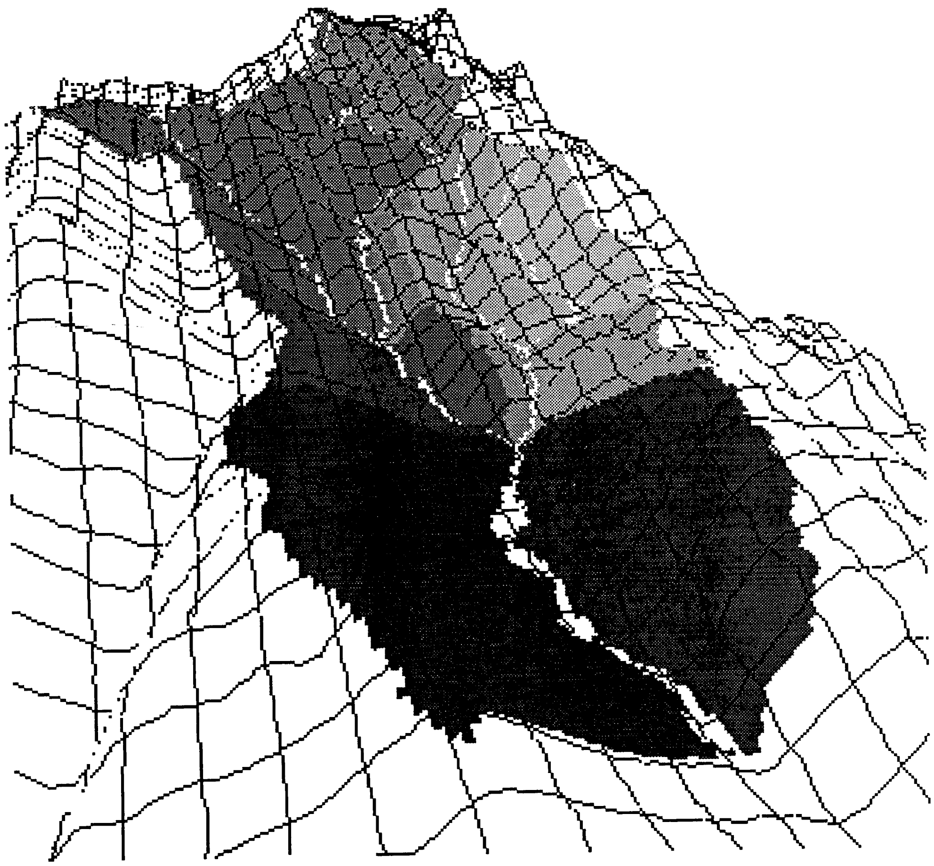


Fig. 5. Representation of the North Fork of Elk Creek by seven stream links and 14 hillslopes. Hillslopes are simply defined as the area draining into a stream link from one side.

Montana, into seven stream segments (referred to as links) and 14 hillslopes (two per link). The number of hillslopes covering an area, and consequently the characteristic size of a hillslope, is dependent on the degree of terrain dissection. As a greater extent of the stream network is represented, greater numbers of smaller, more uniform hillslope units are outlined (Band, 1989a). Larger hillslopes, composed of a number of smaller hillslope facets and stream links include a greater distribution of microenvironments and will have a greater range of energy and mass exchange rates.

The methods of hillslope extraction over a range of scales from digital terrain data use a formal geomorphic model of watershed structure and have been previously described in greater detail (Band, 1986, 1989b). The first step is to extract the stream network. Since the scale of this network determines the scale of the hillslope partition, our object is to produce a

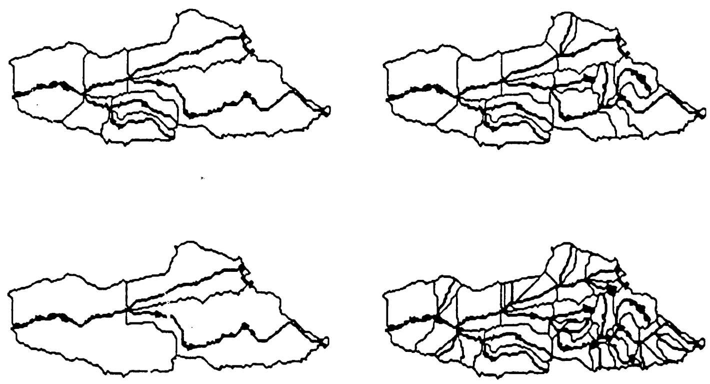


Fig 6. North Fork of Elk Creek partitioned into varying numbers of hillslopes. Clockwise from the lower left: 6 hillslopes, 14 hillslopes, 30 hillslopes and 66 hillslopes.

scale flexible method. This is done by first computing the drainage area upslope of each pixel in the DEM. By setting a minimum threshold drainage area required to support a drainage channel, the scale of the stream network may be defined. Setting a high threshold extracts just the mainstream and those tributaries with the greatest drainage areas, while setting a low threshold produces a much greater number of increasingly smaller tributaries. Any number of partition levels may be produced using these methods (Fig. 6).

Information system structure

A data file (the cartridge file, Fig. 3) is then produced in which each hillslope is a data case for which all model parameters may be recorded. Each hillslope is spatially referenced to the stream network by a topological coding of their parent stream links which allows the determination of any link's upstream and downstream neighbors. This allows the aggregation of individual hillslopes into larger hillslopes or subcatchments, or the segmentation of individual hillslopes into smaller components by extension of the stream network. Landscape units can be continuously redefined by various aggregation or disaggregation procedures, thus forming catchment or watershed units from component hillslopes and stream links. Simultaneously, aggregation or disaggregation operations on recorded data attributes can be used to assign or reform model parameters for the new units. Hydrologic or topographic connectivity is easily accounted for by either using the ordered topologic code described above to find upstream and downstream stream links and using the unique association of hillslopes and subcatchments to the channel links or by explicitly coding pointers to the upstream and downstream entities.

PRODUCTION OF MODEL PARAMETER FIELDS

As outlined above, the spatially variable parameters that must be estimated for each landscape unit are included in the cartridge file describing site specific characteristics (Fig. 3), and a seasonal meteorological file from a nearby base station, including:
- daily precipitation
- minimum and maximum air temperature
- air mass relative humidity or dewpoint
- insolation.

The parameters in the cartridge file are considered fixed over an annual simulation period (assuming negligible change of LAI for coniferous canopies) and are recorded as time invariant attributes for each landscape unit. These values are used by MTCLIM to extrapolate the meteorologic parameters over the set of landscape units. At present, we are operating at scales over which we are assuming that precipitation variation is largely driven by orographic processes which we approximate by an elevation adjustment in MTCLIM. In this section, we describe how the fixed parameters are estimated and how their frequency distributions over the entire basin vary as we aggregate each parameter into mean values for the individual hillslopes over the range of partition scales used.

The topographic information is easily calculated from the DEM. As we are interested in treating each hillslope facet as a data case and simulation unit, we compute the spherical mean surface normal vector to gain the hillslope slope and aspect. This is simply done by aggregating the unit normal vector for all pixels in the slope unit and computing the vector mean. The spherical variance of the surface normals over a hillslope is also computed. All calculations are carried out as discussed by Band (1989a) and Lammers and Band (1990).

Forest canopy LAI is estimated with the use of Thematic Mapper Imagery. Peterson et al (1988) and Spanner et al (1989) have shown that estimates of leaf area index could be generated from TM band 4/3 ratios for conifer forests based on simple regression between sampled conifer stands that cover a range of LAI. This technique is less accurate as the canopy opens as deciduous undergrowth and grass strongly reflect band 4. We have found that normalizing the 4/3 TM ratio with band 5 yields improved results when tested against a set of field sampled tree stands in the area, and we have used this method to estimate LAI. Details of this method are not given here, and will be reported on elsewhere. Fig. 7 shows the distribution of calculated

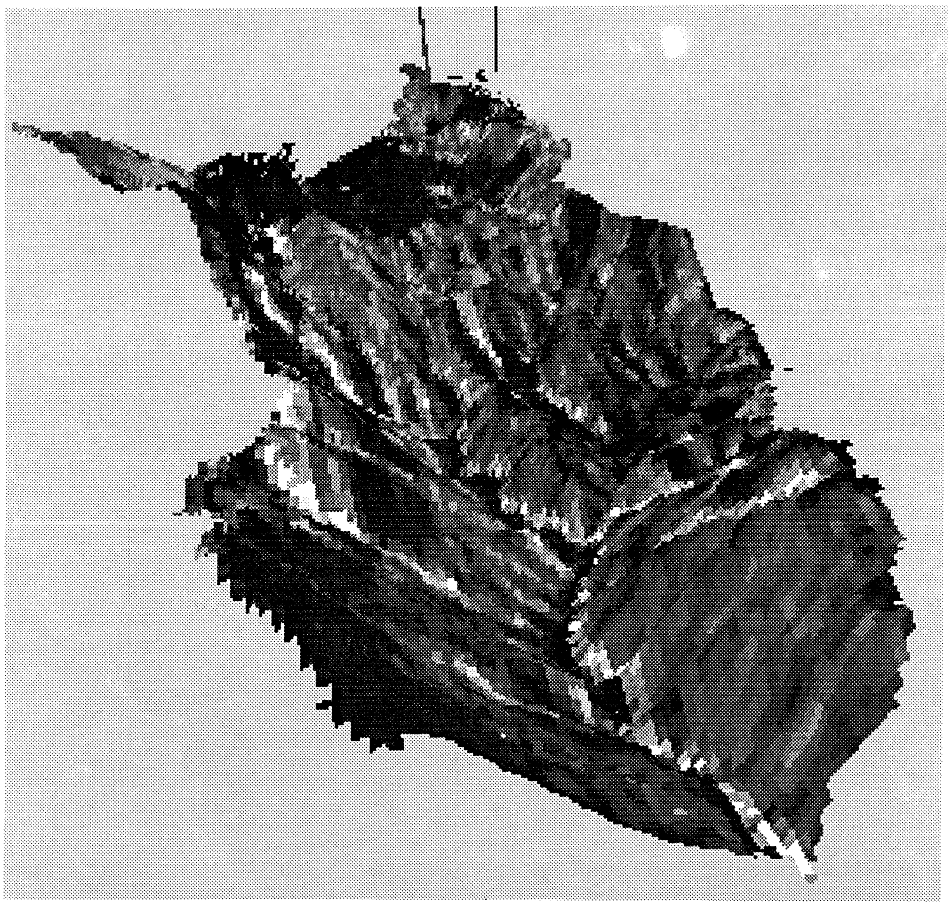


Fig. 7. Perspective of the leaf area index derived from Thematic Mapper Imagery draped over the terrain model.

LAI or the North Fork of Elk Creek. In this set of simulations, we have used mean LAI for each hillslope unit estimated by aggregation of the individual pixel LAI estimates.

A soils map prepared by Nimlos (1982) was digitized, converted to a raster data file and registered to the DEM. The mix of soils found on each hillslope was then found by overlay analysis with the hillslope partition file. Soil water capacities are estimated for the mapped soil series extracted for each hillslope. For each hillslope a weighted mean soil water capacity is computed and used as the single representative value. The range of this value reported for the mapped soil series in the area is approximately 9–17 cm, although it must be borne in mind that these are representative values only and do not reflect the true variability of the soils. It is easily seen in the field that within one mapped soil body, soil depth varies from zero (bedrock outcrops) to over 2 meters (in isolated zones). Therefore, the soils information estimated from the assignment of typical values to mapped soil polygons may strongly underestimate the true field variability of a given property.

As meteorologic variables are only recorded at a base station, site-specific values must be estimated using MTCLIM (Running et al., 1987), which uses meteorological principles including environmental lapse rate, local orographic controls and radiation exposure. At each time step, the base station data are read in and the meteorological parameters for each hillslope are computed. The site-specific meteorologic variables do not need to be recorded in a data table as they can be computed for each time step. If we wish to do a detailed comparison of the seasonal trajectories of ET/NPP along with the driving meteorological variables, then MTCLIM results are written out to a seperate file.

EFFECT OF GEOGRAPHICAL PARTITIONING

The different levels of geographic partitioning and hillslope parameter estimation can produce a range of parameter distributions and geographic patterns. The geographic pattern changes can be regarded as a spatial generalization process, in which the detail of the pattern is varied with the scale of analysis. A constraint on the areal aggregation is the need to maintain low magnitude of the landscape unit parameter variance as incorporated in (4). Recall that it is desirable to have units with a parameter range over which the model is either insensitive or behaves linearly.

For different types of terrain, the manner in which landscape unit variance changes with unit size and shape will strongly influence the efficiency of a given partition strategy. As an example, mountainous landscapes will show a more rapid increase in the variance of solar radiation, vegetation cover and soil water than flatter landscapes as the sampling area increases. For the aggregation step from pixels to hillslopes, Figs. 8 and 9 portray the average LAI variance and spherical variance of the surface normal for hillslopes produced by different levels of aggregation along with the variances generated by aggregating with grid cells over the same scale range. Band (1989a) has previously demonstrated the generation and interpretation of the spherical variance plots in other mountainous terrain. As the mean hillslope size increases, the variances of the mapped variables at first increase rapidly, then asymptotically approach limiting values. The range, sill and shape of these plots are important characteristics of the given type of terrain and may be used as tools to predict the statistical spread of the model parameters within a unit of a given size. This would allow us to

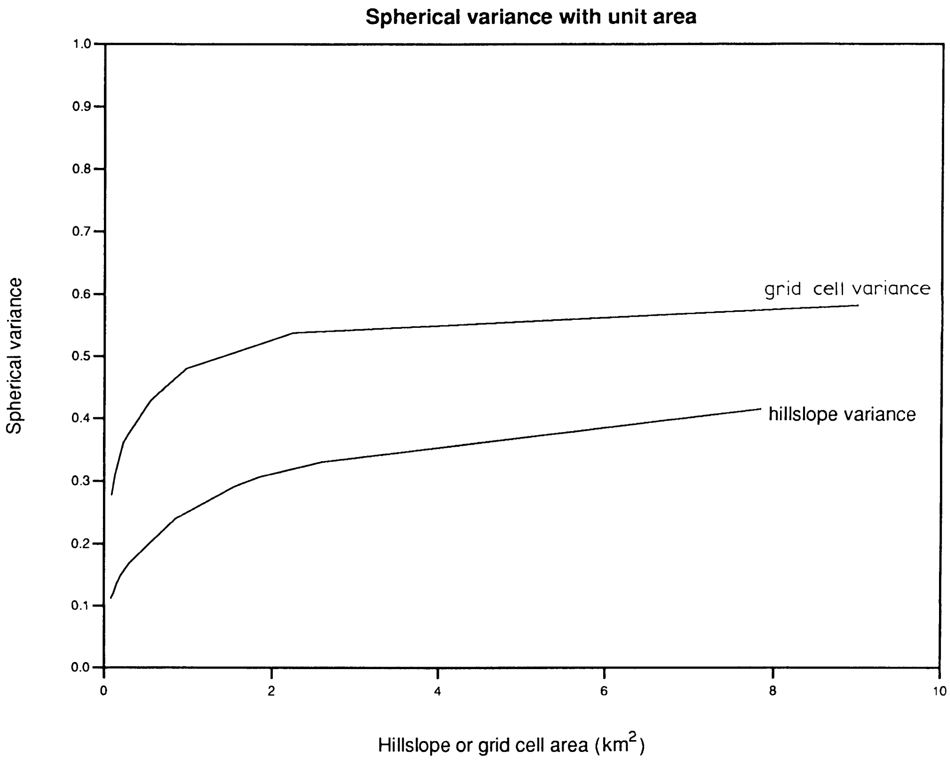


Fig 8. Within-unit spherical variance of the surface normal vectors aggregated over different levels of grid and hillslope partitions.

specify what scale of partition is necessary to gain an admissable level of input variance, considering the nature of the simulation model as given in (2) through (4). Alternatively, given a partition level, we have estimates of the pixel variance for each hillslope unit.

The grid aggregations show similar trends in terms of the rapid approach of the variance to a sill, but also demonstrate a significantly greater variance at each scale than what is achieved by the topographic partition. The higher variances for the grids are due to the inclusion of different slopes with strong microenvironmental gradients. While it may appear intuitively obvious that the topographic partition will show much greater efficiency in comparison with the grid, it is pointed out that the latter is generally the default partition method used in most remote sensing and many GIS studies. This has important implications for the use of moderate to low resolution satellite imagery (e.g. resolution > 1 kilometer) to estimate biophysical parameters. In areas of complex terrain, such as mountainous regions, the values of solar radiation, leaf area index, and soil hydraulic

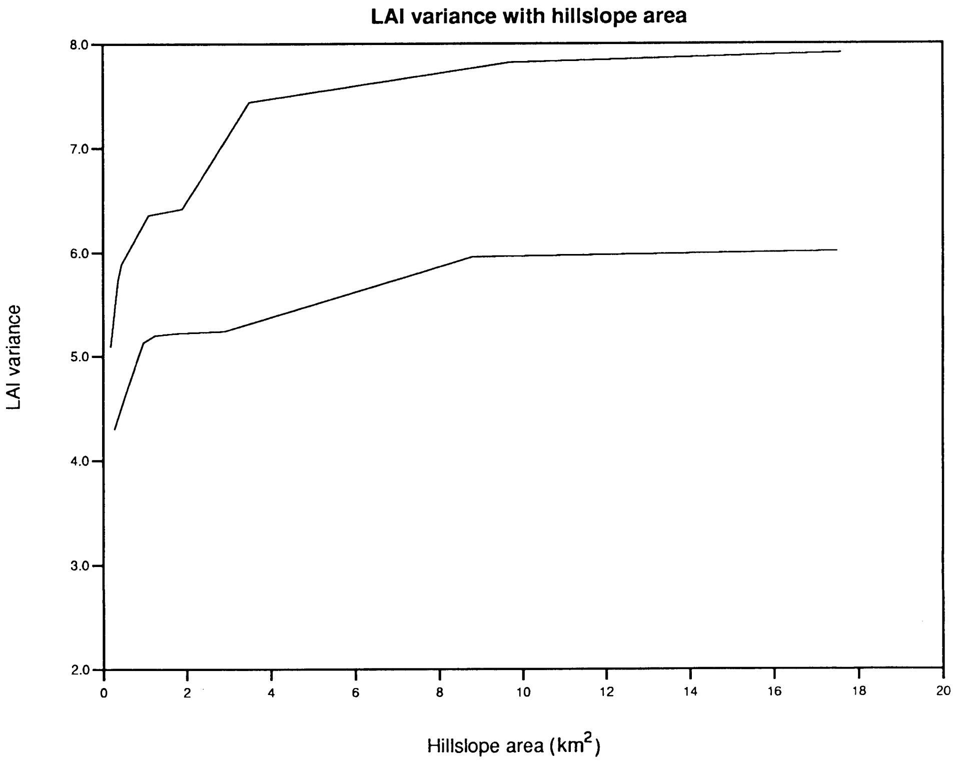
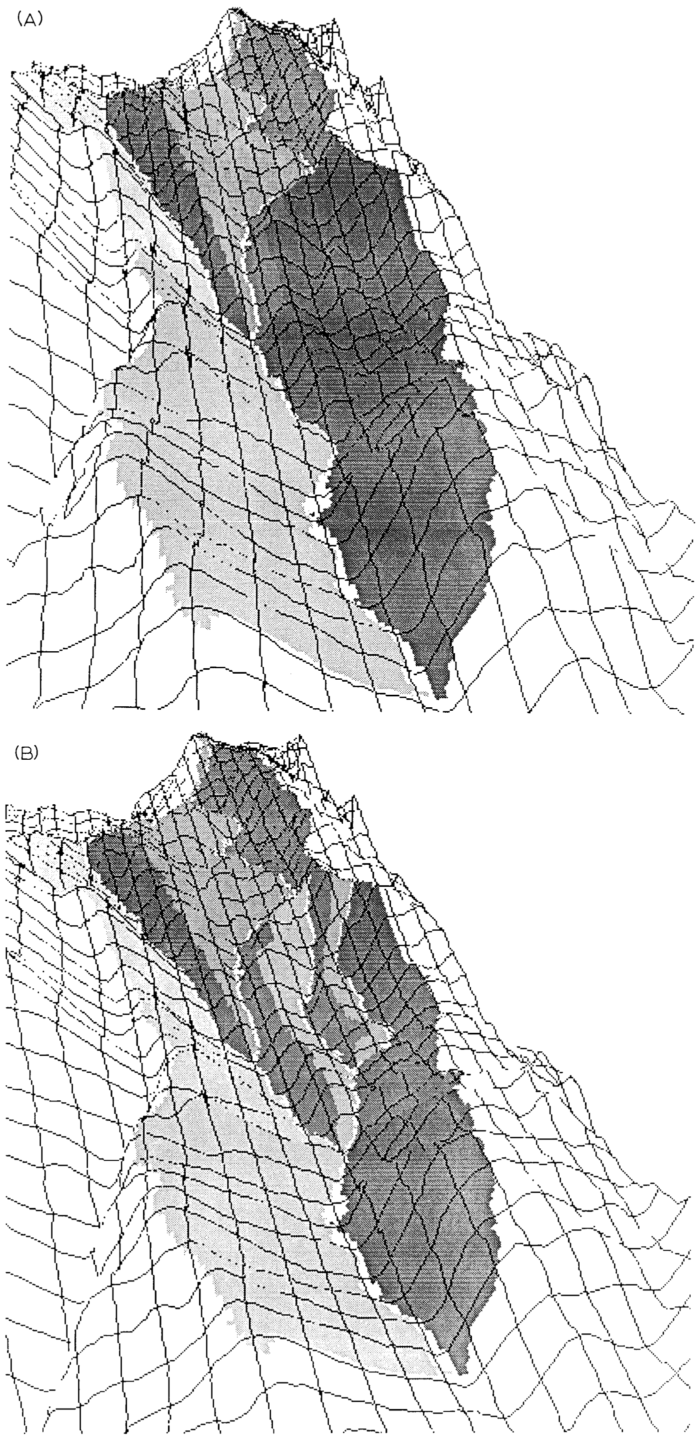


Fig. 9. Within-unit variance of leaf area index aggregated over different levels of grid and hillslope partitions.

parameters may be quite variable and intercorrelated within the area of a single pixel. Indiscriminate use of the single observed or derived value for each parameter without incorporating variance and covariance information as in (4) may lead to significant bias in modelling surface processes.

MULTI-SCALE SIMULATIONS

Three sets of surface parameterizations and simulations were prepared and run for the North Fork of Elk Creek. Figure 10a–c shows the annual evapotranspiration simulated for the North Fork of Elk Creek with three levels of hillslope partitioning. All simulations use the same 1988 meteorological record. For partition levels of 6, 14 and 30 hillslopes, the computed range of annual ET are 38.8–51.9 cm, 38.9–51.9 cm and 26.0–51.8 cm, respectively. The increased range for the 30-slope partition is due to the ability to resolve hillslopes within the burn area shown in Fig. 7. Inspection of the cartridge files (Table 1) for the three partitions shows that the much


(A)
(B)

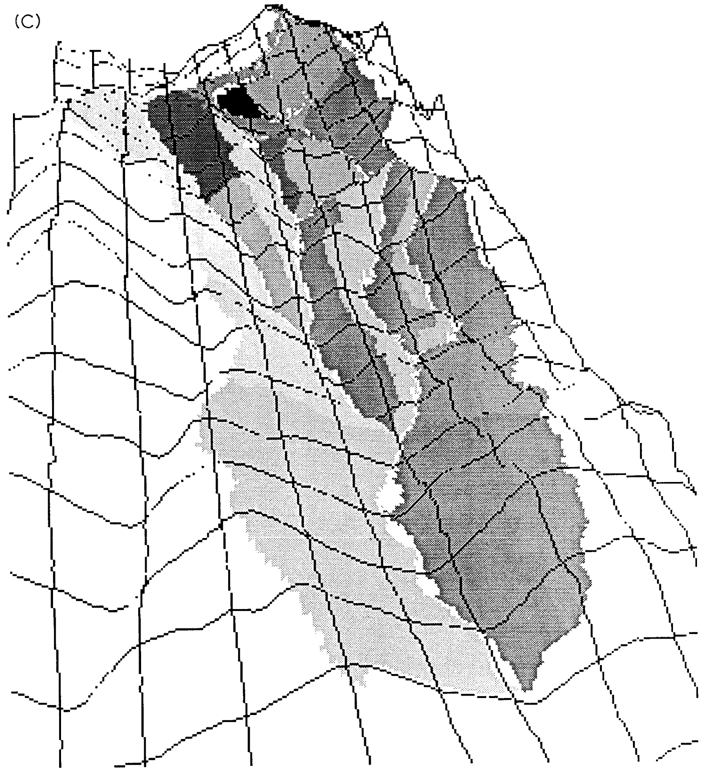


Fig. 10. Cumulative annual evapotranspiration simulated over the North Fork of Elk Creek distributed over (a) 6, (b) 14, and (c) 30 hillslopes.

lowers LAI values in the burn area (e.g. slope 22 in the 30-hillslope partition) averaged out in larger hillslopes in the six-slope and 14-slope partitions.

The hillslope area weighted mean ET for these three simulations were, in order, 43.8 cm, 43.4 cm and 41.6 cm. The small range of these mean ET values suggests that there is little model sensitivity to the parameterizations derived from the different levels of the watershed hillslope partitions used here. It is further suggested that the changes to the empirical distribution functions of the model parameters over the three partition levels are symmetric in their effects on simulated ET, such that additional microenvironments revealed at higher resolution that produce higher values of ET are offset by microenvironments producing lower ET. Simulated PSN follows similar, although not precisely parallel, trends.

Generally higher annual ET on south-facing slopes in this water-limited environment can largely be attributed to the predominance of lower SWC and solar radiation on north-facing slopes. It is possible that the resolution of the major north-south slope differences is sufficient at each of the three partition levels. The major differences in ecosystem structure and process is

TABLE 1

Cartridge file for 6,14 and 30 hillslopes

Aspect	Elevation	Gradient	LAI	SWC	Slope #	Slope area
Six-hillslope partition						
183.2	1440.4	19.3	5.85	0.138	1	2.80
324.6	1459.4	27.8	5.97	0.118	2	4.54
187.5	1749.6	22.1	7.41	0.138	3	2.04
303.6	1726.5	19.8	4.87	0.115	4	1.13
228.9	1768.5	28.5	4.54	0.127	5	3.51
326.7	1789.1	18.4	6.09	0.109	6	2.87
Fourteen-hillslope partition						
183.0	1422.0	18.7	5.72	0.134	1	1.88
358.1	1386.5	22.6	6.39	0.109	2	1.15
183.6	1478.2	20.7	6.12	0.145	3	0.91
323.8	1389.7	19.6	6.13	0.114	4	0.32
187.5	1749.6	22.1	7.41	0.138	5	2.04
303.6	1726.5	19.8	4.87	0.115	6	1.13
228.9	1768.4	28.5	4.54	0.127	7	3.51
326.7	1789.1	18.4	6.09	0.109	8	2.87
229.3	1398.4	15.3	6.06	0.136	9	0.12
18.3	1423.1	16.8	6.31	0.117	10	0.68
236.3	1543.6	19.7	5.75	0.138	11	0.56
318.0	1515.7	18.2	5.66	0.116	12	0.40
251.7	1535.4	17.5	5.34	0.129	13	0.32
329.8	1512.8	18.3	5.53	0.109	14	0.79
Thirty-hillslope partition						
183.0	1422.0	18.7	5.72	0.134	1	1.88
358.1	1386.5	22.6	6.39	0.109	2	1.15
183.6	1478.2	20.7	6.12	0.145	3	0.91
323.8	1389.7	19.6	6.13	0.114	4	0.32
192.8	1623.0	24.0	5.87	0.150	5	0.74
293.2	1581.6	19.6	7.19	0.111	6	0.30
161.4	1826.2	19.8	7.79	0.139	7	0.41
228.5	1796.4	18.5	7.67	0.140	8	0.15
188.5	1828.4	20.0	8.87	0.124	9	0.69
308.4	1779.5	19.7	4.03	0.116	10	0.83
221.2	1586.0	20.0	6.88	0.134	11	0.26
328.7	1537.1	18.0	6.17	0.119	12	0.37
211.5	1732.4	19.0	5.52	0.135	13	0.36
296.4	1703.2	17.7	4.20	0.113	14	0.16
244.0	1703.8	24.0	4.77	0.126	15	0.70
348.8	1730.9	19.3	6.68	0.107	16	0.83
123.4	1768.7	30.4	4.76	0.124	17	0.22
236.9	1763.4	19.7	3.64	0.128	18	0.23
214.8	1746.1	24.8	4.01	0.135	19	0.05
307.8	1802.1	18.6	5.49	0.093	20	0.44

TABLE 1 (continued)

Aspect	Elevation	Gradient	LAI	SWC	Slope #	Slope area
Thirty-hillslope partition						
212.4	1856.1	19.4	3.92	0.121	21	0.47
341.8	1838.5	28.4	2.79	0.111	22	0.28
228.3	1871.8	27.9	4.26	0.138	23	0.53
318.0	1900.1	16.5	5.87	0.112	24	1.22
229.3	1398.4	15.3	6.06	0.136	25	0.12
18.3	1423.1	16.8	6.31	0.117	26	0.68
236.3	1543.6	19.7	5.75	0.138	27	0.56
318.0	1515.7	18.2	5.66	0.116	28	0.40
251.7	1535.4	17.5	5.34	0.129	29	0.32
329.8	1512.8	18.3	5.53	0.109	30	0.79

Aspect: degrees clockwise from grid north.
Elevation: meters above sea level.
Gradient: degrees.
LAI: dimensionless.
SWC: meters.
Slope area: square kilometers.

represented at the coarsest level and only details of small microenvironments are added at the finer resolutions. The shifts in the values and ranges of simulated ET correspond to different mixtures of mapped soils, exposure, and LAI that are incorporated into each set of hillslopes. More detailed decompositions of the terrain reveal a greater distribution of microenvironments and lead to a greater range of the simulated processes. These distinct microenvironments are lost when the surface parameters are averaged over fewer, larger units as a large proportion of the parameter variance corresponds to high-frequency topographic and forest cover changes in this mountainous environment.

Although the gray scales of Fig. 10a–c are adjusted to the simulated ET range, comparison of the spatial distribution of ET with 30 hillslopes with the six- and 14-unit partitions shows a fundamentally different pattern, with much more distinct behaviour occuring in the smaller catchments resolved on the main canyon walls. While a greater number of simulations must be carried out at different partition levels, it is suggested that certain scale thresholds may exist over which the model parameters and simulation results change rapidly. This may certainly be a function of the size of ecosystem patches, such as the burned area over the headwaters of Elk Creek (Fig. 7) and suggested by the stepped relationship between LAI and partition scale (Fig. 8).

It is reemphasized that these simulations were carried out using mean parameter values alone, without any higher order distributional information.

As the parameter variances decline as we move from the coarser to finer spatial resolutions, we expect the potential bias of the results to decrease. One simple modification to the parameterization procedure shown here would be to make the geographic partitioning of the landscape adaptable to the local parameter variance. Computed parameter means and variances could be used along with some knowledge of the model nonlinearity to control the level of landscape segmentation on a local level. As an example, if a landscape unit (e.g. hillslope) is found to have too high a parameter variance, it could be segmented into smaller units. On the other hand, if neighboring units are found to have similar mean parameter values with sufficiently low variance, they could be merged into a single larger unit. We are currently working on such an adaptable method.

SUMMARY AND CONCLUSIONS

We have described the general outline and approach of a system (RHESSYS) to interface geographic information processing and remote sensing with distributed hydroecologic models for the purpose of large area simulation of biologic and hydrologic flux. The aggregation approach emphasizes the automated partitioning of the surface into a set of functional units that capture the distribution of the important model parameters as between units variance. As the nature of the simulation model defines the significance of the parameters, there is a feedback between model parameter sensitivity, the existing landscape patterns and the efficiency of the various surface partitions.

Surface aggregation is accomplished by redefining the simulation units over a scale range into fewer larger but more complex units. This is done under the constraint of minimizing the internal variance of the objects relative to the sensitivity of the model. To do this we attempt to reproduce the existing landscape architecture with a hierarchy of topographic units which explicitly contain all lowerlevel units as components. Therefore, the geographic pattern of the surface properties at each successive level are captured. We formalize the conditions under which we may use single parameter values to adequately characterize the performance of the finite surface regions. A priori or modeled knowledge of the landscape structure and variance is necessary to predetermine the limiting scale at which this may be achieved in a given landscape.

For our applications, we have used imbedded hillslopes and subwatershed hierarchies to represent the surface. Techniques to track the changes of surface unit distributions of topographic and forest cover parameters (surface normals and LAI) have been presented such that we can estimate parameter variances over a range of scales. While we have presented the basis for evaluating the effects of within unit variability on the presence of bias in process simulations, we need to more carefully assess changes in the multivariate distribution functions characterizing the subunits over scale changes, especially in terms of the degree of nonlinearity in the neighborhood of the solution. More detailed explorations of these properties over a greater scale range and for different terrain types will be the subject of subsequent papers.

The methodology of watershed segmentation shown here effectively discriminates between different microenvironments on the basis of exposure, which often shows a dominant control of ecosystem processes in mountainous terrain. Another important source of variation may be the position along the hillslope in terms of the availability of soil moisture through lateral subsurface soil water flow. In many hilly or mountainous environments, redistribution of soil water during and after storm events forms very noticeable, regular variations in ecosystem processes from top to bottom of the hillslopes. In these cases, we require both a model to predict this redistribution and geographic information processors to extract some index of slope position. We are currently implementing a version of TOPMODEL (Beven and Kirkby, 1979) and the information processors necessary to parameterize TOPMODEL, as a replacement for the current soil moisture accounting routines used in FOREST-BGC. This gives us the capability to further resolve spatial patterns of ecosystem processes within a hillslope system, as well as between hillslopes. At this level of pattern prediction, direct validation of the integrated model with field measurements of a suite of FOREST-BGC/TOPMODEL outputs becomes achievable. Field measurements made at points can be compared to the model predictions at the analogous positions on different hillslopes, and basin integrating measurements of hydrograph parameters can be used to assess larger scale performance. Another advantage is the ability to compare the spatial patterns of ET, NPP or other model products with specific airborne or satellite remote sensing imagery. As an example, ET for leaf water potential (LWP) may be correlated with thermal bands on a very detailed and observable landscape level (from hillslope to hillslope or within hillslopes) as variations in the spatial patterns of the canopy temperature caused by local magnitude of latent heat flux.

At this point we have used the RHESSys methodology on watersheds up to 1600 km^2 in western Montana. We are currently assembling a detailed surface database of an area comparable in size to a GCM grid cell, or a number of mesoscale circulation cells. The database will be used in the development and parameterization of surface hydroecologic models that can be run over regional to subcontinental scales, but can also be locally validated by redefinition of the landscape across this scale range.

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REFERENCES

Abrahams, A.D., 1984. Channel networks: a geomorphological perspective. Water Resour. Res., 20: 161–188.

Band, L.E., 1986. Analysis and representation of drainage basin structure with digital elevation data. Proc. 2nd Int. Conf. Spatial Data Handling, 5–10 July, Seattle, WA. International Geographical Union, Williamsville, NY, pp. 437–450.

Band, L.E., 1989a. Spatial aggregation of complex terrain. Geogr. Anal., 21: 279–293.

Band, L.E., 1989b. A terrain based watershed information system. Hydrol. Processes, 3; 151–162.

Beven, K.J. and Kirkby, M.J., 1979. A physically based, variable contributing area model of basin hydrology. Hydrol. Sci. Bull., 24: 43–69.

Bresler, E. and Dagan, G., 1988a. Variability of yield of an irrigated crop and its causes. 1, Statement of the problem and methodology. Water Resour, Res., 24: 381–388.

Bresler, E. and Dagan, G., 1988b. Variability of yield of an irrigated crop and its causes. 2, Input data and illustration of results. Water Resour. Res., 24: 389–394.

Dagan, G. and Bresler, E., 1988. Variability of yield of an irrigated crop and its causes. 3, Numerical simulation and field results. Water Resour. Res., 24: 395–402.

Lammers, R.L. and Band, L.E., 1990. Automating object description of drainage basins. Comput. Geosci., 16: 787–810.

Meyer, S., 1975. Data Analysis for Scientists and Engineers. Wiley, New York, 513 pp.

Nimlos, T., 1982. Soils of the Lubrecht Experimental Forest. School of Forestry, University of Montana, Missoula, MT.

Peterson, D.L., Spanner, M.A., Running, S.W. and Teuber, K.B., 1988. Relationship of Thematic Mapper Simulator data to leaf are index of temperate coniferous forests. Remote Sens. Environ., 22: 323–341.

Running, S.W., 1984. Microclimate control of forest productivity: analysis by computer simulation of annual photosynthesis/transpiration balance in different environments. Agric. For. Meteorol., 32: 267–288.

Running, S.W. and Coughlan, J.C., 1988. A general model of forest ecosystem processes for regional applications, I. Hydrologic balance, canopy gas exchange and primary production processes. Ecol. Modelling. 42: 125–154.

Running, S.W., Nemani, R.R. and Hungerford, R.D., 1987. Extrapolation of synoptic meteorological data in mountainous terrain, and its use for simulating forest evapotranspiration and photosynthesis. Can. J. For. Res., 17: 472–483.

Running, S.W., Nemani, R.R., Peterson, D.L., Band, L.E., Potts, D.F., Pierce, L.L., Spanner, M.A., 1989. Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation. Ecology, 70: 1090–1101.

Spanner, M.A., Pierce, L., Peterson, D.L. and Running, S.W., 1990. Remote sensing of temperate coniferous forest leaf area index: Influence of canopy closure, understory vegetation and background reflectance. Int. J. Remote Sens., 2: 95–111.