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SPATIAL SCALES AND GLOBAL CHANGE: Bridging the Gap from Plots to GCM Grid Cells

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INTRODUCTION

The complexity of earth system processes results from interactions among the physical, chemical, and biological subsystems that vary in both time and space. Gaining an understanding of these dynamics has taken on great importance in the context of current environmental change and the portent of even larger scale global change. Appreciation for the concept of "scaling" is increasing as we are challenged to integrate data and models from different disciplines and different time and space scales. In particular, biophysical and ecological information, intrinsically derived at the scale of the individual organism, must be extrapolated to the regional and global scales of climate models. Unfortunately, this may not always be a simple process due to complex spatial variations and nonlinearities in dynamics across landscapes. Bridging the gap between our site-level ecological understanding and global scale phenomena challenges our current disciplinary approach and requires new strategies for acquiring and interpreting information on large-scale earth system dynamics.

Research tools such as remote sensing and simulation modeling hold the potential for clarifying general ecological principles by expanding limitations inherent in site-level studies (81, 125). In combination, technologies of remote sensing, geographic information systems, and simulation modeling permit quantitative assessment of the consequences of heterogeneity in earth systems over a broad range of spatial and temporal scales. Remote sensing techniques extend measurements to scales over which biospheric processes operate and provide the only practical means for consistent regional and global monitoring. Geographic information systems (GIS) allow a multivariate approach in the spatial and temporal domains, and simulation models aid in understanding and predicting long-term effects of environmental change. A combination of these technologies is instrumental for linking process-level studies with global scale interests (121, 154)

This paper reviews the experiences of recent attempts to extrapolate local measurements to regional scales through remote sensing and modeling. Issues in scaling and heterogeneity in ecosystems are introduced to provide a theoretical framework, but a thorough discussion of the ever-expanding literature on these topics is beyond the scope of this paper (e.g. see 151). Discussions focus on the roles remote sensing, simulation models, and geographic information systems offer together for the extrapolation of local measurements to regional scales. The discussion emphasizes those parameters that can be estimated remotely and that best assist in scaling of ecological information. Linking current and future remote sensing and GIS technologies with integrative, mechanistic models strengthens our investigations of responses and feedbacks among parameters operating at different scales, and improves predictions and understanding of biosphere/atmosphere interactions. Strategies for scaling process-level studies must be considered by the interdisciplinary scientific community if any progress is to be made in understanding large-scale phenomena.

PERSPECTIVES ON SCALING

Principal Considerations

Scientists have a natural tendency toward reductionism; we are intrigued by detail and we seek to explain through mechanisms. The key to scaling is determining what to ignore; what we can and cannot ignore affects how easily we move up or down in scale (see 36). Given that ecological systems are scaled in space and time (4), variables influencing a process may or may not change with scale (150). A shift in the relative importance of variables may result from the influence of additional factors and constraints. With our limited "resolving" power—i.e. limited sampling capabilities in both time and space of the frequencies of natural variance—our predictive powers are contingent on an understanding of the characteristic response of processes to changes in scale. In the broad context, scaling requires the identification of process nonlinearities with change in scale, the range in scales where linearity may hold, and the properties that may be coherent between scales. The object, then, is not to analyze all of the smaller-scale aspects of a process under observation, but to focus instead only on those that have direct importance to the scale under consideration (15).

Hierarchy theory serves as a framework to approach complex systems (4, 104) by considering only factors that are "operationally" significant. An important consequence of hierarchical structuring is embodied in the concept of constraint (103). The scale under observation is affected by the potential behaviors of its components and by the environmental constraints imposed by higher levels. Lower-level dynamics are too fast to be seen as variables; they are experienced as averages or integrated values and appear in patterns as a blend. These dynamics can often be ignored, given a relatively stable system (103). Reciprocally, higher-level dynamics are so slow that they are experienced as constants, and larger-scale spatial patterns are seen only as a uniform, local condition. However, when the system is disrupted, it is the response dynamics at the fine scales that break up the constraint system and move the system into a new configuration (103). Similarly, coupling large-scale models such as general circulation models (GCMS) with important subsystems such as biology is important to understanding the complex of regional and global process interactions and the integrity of their connections under directional environmental change (125).

Spatial heterogeneity constrains our ability to translate information from one scale to another. Scaling problems may not occur in spatially homogeneous systems because process measurements are likely to sum directly. However, in heterogeneous landscapes or aquatic systems, process measurements obtained at fine scales often cannot be summed directly to produce regional estimates because of the large number of interactions involved and the spatial heterogeneities that may influence processes in nonlinear ways (76, 116). Top-down approaches such as remote sensing must consider nonlinearities that may enter into coarse resolution measurements.

The response of a process to changes in scale can be defined as one of four conditions (43): (i) The process under consideration is invariant with scale, in which case no transformations are required. (ii) A process is similar in its effect across scales (e.g. a linear relationship) and scale transformations are simple. (iii) The process varies little and remains dominant across scales, but additional factors and constraints increase uncertainty of the prediction process. (iv) The importance of the process or the process constraints changes with scale. In both cases (iii) and (iv), inappropriate characterization of local scale processes may introduce substantial error in large-scale extrapolations (42, 75, 76, 116). Case (iv) may require the identification of critical thresholds below or above the observation scale for any sort of successful extrapolation (e.g. 43, 77).

In sum, to understand the response to change in scale we must acquire a quantitative understanding of: (i) the heterogeneity of the system under observation (frequencies of natural variation), and (ii) the linkage between spatial and temporal patterns and the processes that drive them. Given such knowledge, scaling from the plot to the GCM grid cell is a matter addressed (when extrapolations are complex) in the initial model formulation using hierarchy theory, or it is a problem in sampling strategy.

Integrating Perspectives: Bottom-Up and Top-Down

Scaling represents the transcending concepts that link processes at different levels of space and time (19). It implies a change in scale by identification of significant (often limiting) factors at each scale under consideration; the approach can be in an upward or downward direction. The bottom-up approach begins with individual or entity-based (e.g. communities, functional groups) measurements and adds appropriate constraints to explain phenomena observed at broader scales. The objective is to use information that is available at fine scales to predict phenomena at broader scales for which empirical data are lacking. Errors will occur if predictions do not take into account changes in process response or the appearance with change in scale of new constraining factors.

The top-down perspective begins with an observation, makes a generalization, and proceeds to describe the mechanism. In other words, this approach analyzes the pattern and infers the processes that generated the pattern. The concept of constraint can be used to predict phenomena at finer scales with the objective of identifying the factors that have the most control over variation at each scale. Error in this approach arises because of an inability to address heterogeneity or because of increases in variance coming from the bottom up; the question is to determine whether variance is subsumed or expressed at each higher scale.

Parallel approaches (bottom-up and top-down) to system processes may be taken by different sciences, but unless there is some awareness of the significance of scale and its consequences for interpretation, conflicts will occur with regard to extrapolation and prediction (68). While we can describe mechanisms using the scaling-up approach, we identify, from the top down, prevalent patterns which result from the feedbacks that may subsume much of the variation in those mechanisms (155). Coherent connections between small-scale site specific measurements and regional scale phenomena require the concurrent implementation of bottom-up and top-down approaches. Complex scale interactions will demand direct observations at both small and large scales; knowledge of small-scale dynamics will not be enough to predict large-scale processes (43).

Remote sensing involves both scaling-up and scaling-down processes. The synoptic nature of remotely sensed data presents the top-down modeler with large scale measurements of pattern. The resolution or grain size is immediately as large or significantly larger than the traditional field plot size, and it samples the landscape in a manner that may or may not represent natural

frequencies of interest. Scaling-up becomes relevant in the attempt to understand the relationship of the measurement to surface conditions. This is a function of the surface reflectance properties and sensor optical characteristics; time-series measurements and the confounding influence of atmospheric conditions; and the influence of heterogeneity within the landscape relative to the pixel size.

ECOSYSTEM STRUCTURE, DYNAMICS, AND CHANGE

Ecosystem Processes over Time Scales of Global Change

The biotic response to and feedback on global environmental change is expected to vary on many scales. Recent research has emphasized short-term atmosphere-biosphere interactions at time scales of one to several years. There is general agreement that increasing global carbon dioxide concentrations will have direct physiological effects on plants, but the duration of these effects and their expression at the level of the population and ecosystem is relatively unknown (13, 36a, 50, 141). Biogeochemical and biogeographical relationships are likely to be affected over decades to centuries (125). Yet, while carbon and nutrient dynamics can be expected to be sensitive to changes in temperature and precipitation regimes, the complexity of response will vary between ecosystems (26, 45). Land management in agroecosystems may induce enough change in regional carbon balance to overshadow predicted climate change effects (17). Strong evidence suggests that land use changes that affect vegetation canopy characteristics and evapotranspiration will influence regional and perhaps global climate (34, 111, 134, 142). Alterations in disturbance regimes (e.g. severe storms, fires) may seriously influence ecosystem composition and functioning, and the prediction of potential species redistribution will likely be further confounded by the rate of climate change and spatial displacement of habitats (22, 27, 28, 107).

Efforts to predict the effects of global environmental change must consider the coupled nature of earth system components, namely, the hydrosphere, biosphere, and the atmosphere (125). Studying these interactions at landscape to global scales will require the integrated use of remote sensing, GIS, and simulation models. But because models have been parameterized with traditional environmental and biometeorological data, incorporation of spatial data bases and remotely sensed information requires reevaluation of both the biological/climatological processes and the qualitative and quantitative data types needed for large scale simulations. Successful modeling of biospheric-atmospheric interactions will need to consider the range of time steps at which interactions occur. These can be represented in essentially three characteristic time constants: (i) high frequency (seconds to days) physiological or biophysical processes, (ii) middle frequency (weeks to seasons) phenology and carbon and nutrient dynamics, and (iii) low frequency (annual to decadal) ecosystem compositional and edaphic changes (67). Data requirements at each of these scales have been recognized by the international community (67), and efforts to assemble relevant data bases are gaining momentum.

Spatial and Temporal Characterization

The current scientific data base is inadequate to address much of the spatial and temporal heterogeneity encountered at regional and global scales. Early efforts to assemble terrestrial vegetation and soil data sets at 1° latitude by 1° longitude resolution (87, 164) have contributed significantly to the incorporation of realistic biological regimes in modeling of climate processes (e.g. 40). Improved global land cover characterization and monitoring by remote sensing is feasible (144), but other global data sets such as land use, disturbance history, and physicochemical soil attributes will require substantial resource investment in the compilation of existing data and future ground-based measurements. These data sets must include mesoscale landscape characteristics and knowledge of their change over time for successful generalization to the global system (111).

Studies that link ground observations to regional and global scales are needed to take full advantage of the broad base of understanding at smaller scales. Research programs that coordinate simultaneous, integrated measurements across a range of scales are required to characterize spatial and temporal scales of variability (54). Several recent field programs have been specifically aimed at the scaling issues associated with a spatially heterogeneous environment. The First ISLSCP (International Satellite Land Surface Climatology Project) Field Experiment (FIFE) was designed to address, through simultaneous acquisition of satellite, atmospheric, and surface data, processes controlling surface energy and mass exchange over a range of scales, from those of individual plants to scales of GCM grid cells (53, 132). The Hydrologic Atmospheric Pilot Experiment (HAPEX) was a similarly intense measurement campaign for the study of the water budget and evaporation at climatic scales (5). Regional-scale studies of biosphere-atmosphere interactions on the chemistry of the troposphere over relatively undisturbed tropical forests and wetlands (Amazon Boundary Layer Experiment, ABLE) are part of a longer-term study of tropospheric chemistry supported by the Global Tropospheric Experiment (GTE) component of the US National Aeronautics and Space Administration (NASA) Tropospheric Chemistry Program (55, 56). These and other similarly designed experiments provide critical links between small-scale, process-oriented biogeochemical research and modeling at global scales.

Priorities for future comprehensive, multiscale studies need to be placed on regions expected to have the maximum potential for change, including tropical moist forest and savannah regions and northern-latitude tundra and boreal ecosystems (54). The second major ISLSCP experiment to be conducted in North America will focus on the latter. This Boreal Ecosystem-Atmosphere Study (BOREAS), planned for 1994–1996, will provide the integration in large-scale field experiments of biogeochemical objectives (e.g. GTE/ABLE) and biophysical objectives (e.g. FIFE) that has previously been lacking (54).

REMOTE SENSING-BASED EXTRAPOLATION MODELS

Extrapolation is the process of estimating unknown values from known conditions through the transfer of information from one scale to another or from one system to another at the same scale (150). Again, the heterogeneity of the system and the scale dependence of the process under question will dictate the ranges over which extrapolations may be made. Because of the wide variation in states and processes across temporal and spatial scales, extrapolation from local to regional and global scales appears an impossible task based on strict statistical requirements. Optimally, sampling techniques should involve (i) systematic and repetitive measurements to evaluate the variability of the data; and (ii) random sampling to provide a picture of the heterogeneity of the data (7, 70). For determination of regional processes, this would entail more ground sampling than is logistically possible for validating model predictions. Remote sensing can overcome these constraints to a certain extent by providing a means of sampling large areas repeatedly over time. The type of biophysical and geophysical attributes sensible from space will determine how widely ecological extrapolations can be implemented; and the calibration of the data between instruments and across time will affect how consistent those extrapolations will be.

The focus in research using remote sensing data has shifted over the last decade from empirically based classification and mapping procedures to more physically based characterization of the data with regard to radiative transfer and energy balance. Mapping and inventory remain important applications that are particularly relevant for tracking regional and global change. Through statistical classification procedures, remote sensing has been used to describe the spatial patterns in land cover types, their location, area, and change over time (e.g. 60, 62, 118). Modeling of structural characteristics of the canopy such as crown shape, size, and spacing by using radar (e.g. 89, 143) and optical remote sensing systems (e.g. 79, 80, 136, 137, 160) promises to both augment and refine classifications by providing more quantitative information on ecosystem structure. Applications to process-level questions will require explicit linkages between the process under study and spatial (and temporal) landscape patterns. Quantitative remote sensing that relates the biophysical and geophysical attributes of the surface (e.g. reflectance, phase, and backscatter) to physical units (e.g. biomass, absorbed photosynthetically active radiation (APAR), evapotranspiration) has already demonstrated potential to drive ecosystem and climate models (40, 123). Remote sensing can provide time-series data as additional input to models, allowing representation of pixel-to-regional scale variation with improved temporal accuracy.

Remote sensing data will be needed for extrapolations in three areas of relevance to global change research: (i) physical processes linking the biosphere to the atmosphere; (ii) biogeochemical cycling, including trace gas exchange; and (iii) ecosystem dynamics and change over time. Each of these will likely have profound influence on the others (e.g. ecosystem structure will influence rate and magnitude of biophysical processes). The following discussion reviews a number of parameters retrievable from remote sensing data that will be be important to scaling ground-level understanding in one or more of these three areas.

Biophysical Processes

Important interactions between the land surface and the atmosphere involve the exchanges of radiation, sensible heat, latent heat, and momentum. Until recently, these processes have been modeled at global scales in a very rudimentary fashion (see 33, 130). Incorporation of explicitly modeled vegetation effects in descriptions of land surface characteristics that govern albedo, roughness, and moisture availability has brought GCM simulations significantly closer in agreement with observations (34, 133, 142). Remote sensing can integrate the relatively small-scale understanding on which the modeling of these processes is based to the appropriate scales required for initialization of atmosphere-biosphere interaction models. There is promise that some of the components of the radiation budget and surface roughness can be estimated using a number of different sensors (69, 99). The following discussion focuses on attempts to remotely estimate the biophysical controls over evapotranspiration.

The idea of remote sensing as a fundamental tool for scaling biophysical rates of photosynthesis and transpiration has drawn on the simple thesis that plant growth is related to the fraction of incident radiation absorbed by the canopy and the dry matter:radiation quotient (an "efficiency" coefficient defining the carbon fixed per radiation intercepted) (96, 97). Chlorophyll's unique absorption of energy in the red (R) spectral region relative to the highly reflected near-infrared (NIR) region distinguishes live vegetation from soil and other nonphotosynthetic materials. Early field studies investigated the near-linear relationships between spectral reflectance indices composed of radiance measured in those regions (e.g. a simple ratio NIR/R or normalized difference vegetation index (NDVI = (NIR−R)/(NIR+R)) and standard measurements of the canopy properties of biomass, leaf area, and photosynthetically active radiation (PAR) absorbed by the canopy (8, 58, 59, 146, 147). Strong relationships were later demonstrated between time integrals of satellite-derived vegetation indices (VI) and net primary production (NPP) (40, 47), the geography and seasonality of vegetative cover (73, 149), and simulated photosynthesis and transpiration (122).

The amount of leaf surface area available for gas and moisture exchange (described by leaf area per ground area, the leaf area index—LAI) has been shown to relate linearly to NDVI (see 9, 109, 124), although changes in canopy closure, understory vegetation and background reflectance may affect broad-scale extrapolations (10, 138). VIs are, in fact, asymptotic in nature with respect to LAI, with linearity extending from LAIs of 2 to 6 for crop and grassland canopies (8, 119, 146, see also 131) and up to approximately 8 for coniferous forests (110, 123).

Theoretical analyses by Sellers (128) examined the links between spectral vegetation indices and canopy properties of LAI, absorbed PAR, photosynthetic capacity, and minimum canopy resistance. A mechanistic basis for the observed correlations (given a horizontally uniform canopy) was demonstrated with a two-stream approximation model of radiative transfer and simple leaf models of photosynthesis and stomatal resistance (129). The analysis suggested that VIs are indicative of instantaneous biophysical rates of photosynthesis and conductance but are not a reliable estimator for any state (leaf area, biomass) associated with vegetation. These arguments were a significant advance in theoretical understanding of remote sensing measurements, but problems associated with inadequate physiological models and optical contributions from variations in background and canopy architecture were admitted weaknesses.

The potential for scaling estimates of photosynthetic rates and conductances using VIs was defended more rigorously in work by Sellers et al (131). In the simpler model (129), it was assumed that all leaves in the canopy had the same light response curve, i.e. all leaves throughout the depth of the canopy responded identically to the flux of PAR. Accordingly, with increasing PAR flux above the canopy, the uppermost leaves would saturate and leaves lower down would remain below saturation, resulting in an increasingly nonlinear relationship between photosynthesis and the fraction of absorbed PAR. By considering that photosynthetic capacity changes in parallel with the depth-distribution of PAR (14), the bulk analytical canopy model of Sellers et al (131) closely reproduced an exact numerical integration of leaf models for normal environmental conditions. The modified model produced a stronger theoretical relationship between canopy biophysical rates (photosynthesis, conductance) and spectral VIs because the contributions of canopy structure and environmental forcings could be separated from those of leaf physiology and radiation flux. This argument supports the original hypothesis that area-averaged spectral vegetation indices do give good estimates of the area-integral of photosynthesis and conductance even for spatially heterogeneous (although physiologically uniform) vegetation covers.

Conditions still constraining the predictive powers of VIs include those that affect the photosynthesis/PAR relationship such as stressed vegetation and differing photosynthetic pathways (C_3, C_4), and conditions that may influence spectral estimates of absorbed PAR such as contributions from background soil and litter. The former can be addressed by considering the range of biological processes for different vegetation types and their respective sensitivity to VIs and environmental variables (12). For example, land cover can be stratified according to ecosystem or biome type before relationships are established between PAR and VIs. Fung et al (40) determined global net primary production from NDVI using an empirically derived scaling factor that essentially accounted for Monteith's conversion efficiency for each biome type. Prince (113) has cited efficiency factors converting annual APAR energy in megajoules (MJ) to NPP in grams for different biome types.

However, it is questionable whether a measurement in two spectral bands can provide an unambiguous measure of vegetation. Confounding influences from background variation, atmospheric attenuation, and off-nadir viewing cannot all be accounted for using a two-band ratio (10, 21, 46, 66, 93, 140). Huete (64) suggests a simple adjustment of VI to account for first-order soil-vegetation interactions (i.e. soil brightness effects); but secondary soil variations due to soil optical properties can only be addressed, using multiple spectral bands, through factor-analytic inversion models which allow composite plant-soil mixtures to be separated into component spectra (63, 65). In a similar approach, spectral mixture analysis systematically separates and quantifies vegetative and nonvegetative components at sub-pixel spatial resolution by identifying major sources of variance in remote sensing imagery (3, 135, 136, 137, 152, 153).

Understanding of the relationship of biophysical and biochemical processes to canopy reflectance is being extended by use of more defined measurements of spectral curvature available from high spectral resolution instruments. Variables of spectral shape such as width, depth, skewness, and symmetry of absorption features may be more directly indicative of biochemical state and canopy physiology than are broad-band measurements made with current operational sensors (see 156). Wavelength-specific absorption differences among photosynthetic pigments may permit quantification of their concentrations, and these may be related to photosynthetic activity (e.g. 30). In one case, a spectral change in green reflectance resulted from a light-induced change in a xanthophyll pigment that is closely linked to changes in photosynthetic capacity (41). Studies relating chlorophyll content to the location of the inflection point of the long wavelength edge of the feature

have met with varied success (24, 94, 120, 126). Second derivatives of high spectral resolution reflectance data in the visible and near infrared regions appear to be strongly related to absorbed PAR and relatively insensitive to the reflectance of non-photosynthetically active materials such as litter and soils (52).

Biogeochemical Cycles

ELEMENTAL CYCLES Terrestrial carbon dynamics have presented significant challenges to global carbon cycle research. The magnitude of the terrestrial carbon pools varies in time and space, and the balance between the principal acting processes—namely, carbon assimilation by photosynthesis, respiration rates, and carbon turnover time—determine the net exchange between the biosphere and the atmosphere. Remote sensing can contribute information that can aid our understanding of these processes and their response to and feedback on the global system. Research linking reflectance measurements to photosynthesis and net primary production, reviewed in the above section, will be instrumental in the inventory of global terrestrial carbon. Some of the terms used to calculate carbon turnover time, nutrient availability and soil respiration may be provided by new techniques in imaging spectrometry. These processes are tightly linked with rates of decomposition, which are strongly regulated by the chemical quality of the organic matter (e.g. 91, 92). Remotely sensed estimations of lignin (the most recalcitrant material in litter), canopy nitrogen, or other constituents may serve to constrain decomposition submodels in ecosystem simulations, thus stabilizing model inversions (2, 125).

Quantitative determinations of vegetation biochemistry from reflectance data were initiated in the agriculture and the food industries (e.g. 102, 161) and later adopted by ecologists to replace standard laboratory wet chemistry analyses of lignin, cellulose, and nitrogen (90, 158). The physical basis for the extraction of biochemical information is the absorption of radiation by the molecular functional groups of C-H, O-H and N-H found within all foliar material. Overtone and combination bands specific to these compounds occur in the near infrared region and are particularly sensitive to changes in chemical concentrations. Principles of analytical spectroscopy concerned with separating individual component concentrations from organic mixtures (see 156) are currently being tested on reflectance data from field and aircraft spectrometers. An early application of NASA's Airborne Imaging Spectrometer (AIS) data successfully estimated canopy lignin concentrations in a series of northern temperate forest ecosystems and was subsequently used to derive images of annual nitrogen mineralization rates (157, 159). While the rate of nutrient cycling is influenced by a host of factors, foliar lignin is particularly dominant in modulating litter decomposition and therefore cycling rates in forest ecosystems. In this case, lignin provided the scaling factor and remote sensing the means to extrapolate beyond site measurements in order to observe variation in nitrogen availability at the scale of the landscape.

Further studies on the question of remote sensing of canopy chemistry are currently underway (20, 25, 44, 83). The nature of the remote sensing problem requires consideration of additional parameters beyond those used in the field of analytical chemistry. In the complete leaf or canopy condition, complications arise from the attenuation and multiple scattering of radiation along the path length, additional influences from soil, shadow and other background components, and atmospheric scattering and attenuation of the reflected signal. In the spectral region beyond 1 μm, the spectral reflectance of plant canopies is dominated by liquid water absorption features. The absorption intensity of the spectral features associated with canopy biochemical constituents can be quantified only after the effects of liquid water absorbance have been removed (44). Curve fitting techniques are used both to correct for the effects of liquid water (41a) and to solve for the canopy biochemical constituent concentrations. The accuracy of these techniques is dependent on the noise level of the spectral data. Thus, determinations of canopy biochemical constituent concentrations that are based on spectra derived from multiple pixels are more accurate than those performed on single pixels. The application of spectral unmixing techniques (e.g. 136, 137, 153) to derive end-member spectra and their spatial abundances can be used to provide low noise spectra for the curve fitting analysis. It also has the additional benefit of reducing the number of spectra for which the curve fitting analysis must be performed from a million or more (the number of pixels in a typical imaging spectrometer scene), to the number of spectral end-members.

The successful use of remote sensing in extrapolation models of biogeochemistry will depend on relating measurements to ecosystem properties indicative of underlying processes. This will, of course, require a better understanding of how those properties, such as plant physiology and biochemistry, reflect the balance between factors limiting to the system (125).

TRACE GAS EXCHANGE Considerable attention has been placed on predicting the effects on climate of increasing concentrations of radiatively active trace gases (see 95). Attempts to develop regional and global budgets of biogenically released trace gases have been made (see 74), but source/sink strengths and the processes that control flux rates remain areas of great uncertainty. This is largely due to the complexity of the biological, physical, and chemical systems that are involved and the difficulty of measuring exchange fluxes in the field (see 6). Significant effort has been given to understanding and quantifying flux processes within important ecosystems such as wetlands, grassland, tundra, and tropical forest (e.g. 11, 32, 56, 98, 127). However, these studies have disclosed great variability within and among vegetation types as well as with time at a given site.

Regional and global trace gas budgets have been largely based on area-weighted extrapolation of in situ flux measurements considered representative of a given land category. In other words, the region is first stratified into areas considered homogeneous and likely to have lower within-class variance in flux rates. Matthews & Fung (88) demonstrated the importance of wetlands to the global methane budget using a stratification of global wetlands based on environmental characteristics governing methane emissions. The original wetland data base at 1° resolution was developed from global digital data of vegetation, innundation characteristics, and soil properties. The five derived strata were then assigned typical methane fluxes integrated over the methane-production season as defined by latitude.

While useful for first-cut global and regional estimates and for targeting major contributors, area-weighted field estimates can incur significant error from the high spatial and temporal variability in point measurements and the subsequent process of aggregation. An assumption of "representativeness" for the land cover type may fail to account for sources of spatial variation. Matson & Vitousek (84) suggest that the high variability in tropical forests will result in a parallel variability in trace gas fluxes; i.e., there is no representative site for the general category of "tropical forest". Gradients of factors (e.g. soil fertility) that control both fluxes and ecosystem properties and processes in tropical forests may be more useful for extrapolating fluxes and for calculating budgets of nitrous oxide and other trace gases. In fact, stratification of tropical forest types that reflect soil characteristics reveal consistently higher nitrous oxide fluxes in forests on acid clay soils (terra firme) than other forest types within a Brazilian study area, even though within-type variation is significant (85). Estimates of nitrous oxide emission rates in moist tropical forests were extrapolated by areal estimates of forests stratified by soil fertility to derive a tropical contribution to the global nitrous oxide source (86). The total flux, calculated as 2.4 Tg/y, was considerably lower than that based on a general lumping of tropical and subtropical forests and woodlands (7.4 Tg/yr), but the total remains very significant in the global budget. Combination of these types of data with remote sensing-based areal extrapolations may be particularly useful in refining regional flux measurements or locating "hot spots" worthy of further investigation.

Single physical characteristics of the surface in wetlands (water and soil depth, soil temperature) do not appear to be quantitatively associated with the variability of methane flux rates within a single regional wetland system (11), nor have quantitative relationships been found to link wetlands in different physiographic and climatic regimes (88). In the absence of parameters that offer predictive relationships with fluxes, vegetation community distribution can provide a relevant stratification for area-weighted regional flux inventory. An emission inventory of the Everglades was substantially improved by using Landsat Thematic Mapper data to direct in situ sampling efforts in important habitats and by providing a means for calculating area-weighted mean fluxes for the system as a whole (11). Reiners et al (117) followed a similar strategy to predict nitrogen mineralization rates over sagebrush steppe landscape using an ecosystem simulation model parameterized for steppe ecosystem types defined by Landsat Thematic Mapper data.

Aircraft flux measurements provide independent data for testing regional and global extrapolations of trace gas fluxes (31). Regional tower and aircraft flux measurements which integrate gaseous exchange over large areas can provide impetus to relate ground-based measurements mechanistically to regional scales. The Amazon Boundary Layer Experiment (ABLE 2A and 2B) was designed to characterize quantitatively the spatial and temporal variability of trace gases and aerosols over the Brazilian Amazon during wet and dry season conditions (55, 57). Continuous ground-based sampling served to characterize temporal variability, with aircraft and satellite observations providing spatial sampling capabilities. The success of these experiments suggests the use of airborne eddy correlation flux surveys in future research programs to select representative ground sites for continuous tower measurements.

The great uncertainty in estimating global trace gas budgets arises from the heterogeneity of source distributions (56). Difficulties in producing consistent estimates result from (i) high variability in a single habitat, and (ii) uncertainty in geographical extent and seasonal variability in extent of wetland environments. Despite an extensive field sampling program, large sampling errors surrounding ground-based estimates of trace gas emissions occur if the stratification of the area does not consider the controlling factors. Combined remote sensing of landscape biophysical and ecological characteristics and trace gas measurements are needed to generalize to regional and global flux models. Approaches to extrapolations of local to regional measurements should include process-level modeling, stratified sampling by the most relevant landscape units, and synthesis with the aid of geographic information systems (54, 56).

Patterns of Change in Terrestrial Ecosystems

The type and successional stage of ecosystems occurring within a landscape have profound implications for regional biogeochemical flux estimates and atmosphere-biosphere interactions. The rapid rate of land-use changes, particularly in the tropics, contribute directly to perturbations in those dynamics. Ecosystem successional patterns can indicate local variations in water availability and linked carbon and nitrogen cycles, which in turn may modify

the effects of climate change or human disturbance (108). Yet the extrapolation of ecosystem research to regional and global scales has been hindered in the past by the difficulty of observing large-scale spatial heterogeneity and the long-term patterns of successional dynamics (51). Remote sensing and ground-based evaluations provide the most promising tools for compiling geographical information on the stage and condition of ecosystems over time.

The ability to detect long-term change in ecosystems requires that we are able to detect conditions in the static situation, e.g. health, structure, and seasonal productivity (60). Certainly, parameters discussed in this paper, such as seasonally integrated VIs and biochemistry, are variables that will be affected by and respond to environmental change. Image texture combined with spatial statistics provides a means to extract stand structure information from remotely sensed data (e.g. 38, 106). Textural analysis can be considered a quantitative measure of landscape heterogeneity and, when combined with VI data, it successfully documented tallgrass prairie response to burning and grazing treatments (16). Spectral mixture analysis also provides a means to estimate the spatial cover of vegetation in a sparse community, independent of the spectral characteristic of the substrate (136, 137, 152). Procedures have been developed for using the spatial variance in images to quantify the number and spacing of forest trees (37, 79, 80). A ten-year time-series Landsat Multispectral Scanner data was used to track changes in succession state, based on species composition and age structure, for northeastern Minnesota boreal forests (51). Once the images were rectified for changes in atmospheric conditions between years, it was possible to infer the rapid dynamics occurring in the spatial pattern of and the transition rates between forest ecological states.

Reliable information on global land cover/land use maps is a top priority for global change research (67). Existing maps of global vegetation are generally compiled from disparate sources at varying scales and contain many inconsistencies (144). Encouraging results with data from NOAA's Advanced Very High Resolution Radiometer (AVHRR) for monitoring regional land use change (72, 148) and classifying land cover at continental scales (47, 145, 149) suggest that global land cover classification by remote sensing is a real possibility (144). Operational provision of global land cover data will require systems with consistent internal (instrument) calibration, and appropriate temporal and spatial characteristics.

LINKING SIMULATION MODELS AND REMOTE SENSING

The use of remote sensing to drive models will require rethinking of traditional modeling approaches and the use of inverse modeling techniques. This, in turn, will be directed by the understanding of how remote measurements of plant physiology and biochemistry can reflect the balance between above and belowground limiting factors (125). As a consequence, ecosystem simulation models that recognize the relationship between fluxes and controlling factors will be best positioned to link to spatial data provided by remote sensing. While remote observations cannot simulate future change, they will be critical to describe the current state of the earth, monitor near-term change, and estimate initial conditions for predictive modeling.

Pilot efforts have been made to incorporate remote observations as drivers for flux rate calculations. Fung et al (40) integrated global NDVI values with field data on soil respiration and climate data to obtain global distributions of monthly atmosphere-biosphere exchange of CO_2. Satellite-derived LAI has been used to drive simulations of regional evapotranspiration and photosynthesis in a forest ecosystem using a model (Forest BGC) designed to be particularly sensitive to LAI, because LAI can be retrieved by satellite (123). This same model is being implemented as an integrative tool in NASA's Oregon Transect Ecosystem Research (OTTER) project. The goal of OTTER is to examine canopy and landscape characteristics along climate and fertility gradients that may be indicators of ecosystem processes and physiological dynamics. Data is currently being assimilated from the intensive field and airborne remote sensing experiment with the intention of interfacing with Forest BGC and providing a rigorous validation of the flux simulations (e.g. 71). Another NASA project of similar magnitude is the Forest Ecosystem Dynamics (FED) project located in Maine (e.g. 115, 163). This project, concerned with the scaling of ecosystem patterns and processes with northern forests, supports a hierarchy of submodels describing forest growth and development, soil processes, radiative transfer, and establishing functional linkages between them. Multiscale remote sensing acquisitions will serve as inputs to the models, as well as provide, through independent remote observations, validation for the submodels and integrated model.

Simulation models may be useful for developing methods to extrapolate across scales because they can test the implications of various scaling rules. However, ground validations for regional and global simulations are a fundamental problem. Remote sensing can act as an independent validation for spatial predictions from geographically based simulations, and it can test retrospective temporal predictions. Good correlation between time-integrated NDVI and simulated NPP for the central Great Plains indicates the value of remote sensing to verify simulations of important ecosystem dynamics such as productivity (17, 18, 125). As discussed earlier, nonlinear relationships among other processes such as trace gas evolution and soil carbon storage will require more attention to appropriate stratification schemes for spatial extrapolations and inference using remote sensing.

PROSPECTS FOR NEW TECHNOLOGY

Current satellite coverage is of limited use to international scientific needs because many of the measurements are only loosely coordinated in space and time (67). Measurement strategies must be long-term and global, at varying temporal and spatial scales. Remotely sensed data needed for large-scale monitoring and for integration with simulation models requires an observational system that offers: (i) moderate resolution, frequently repeated coverage sufficient to capture rapidly changing biophysical processes; and (ii) high resolution, periodic coverage to assure proper scaling procedures and necessary calibrations at subpixel scales.

Prospects for future remote sensing technology suggest greater capabilities for measuring and monitoring earth system dynamics (99, 105). The Mission to Planet Earth is an international plan to provide comprehensive, long-term, and continuous global observations for the development of quantitative earth system models on both regional and global scales (100). It incorporates both existing and new remote sensing instruments, including the Earth Observing System (EOS), a series of multipurpose polar-orbiting platforms to be initiated in the late 1990s. EOS will offer the first opportunity to obtain frequent (2–16 day repeat) coverage of the earth's surface with remote sensing data at optical, thermal, and microwave wavelengths for a 15-year period (see 162). A data and information system (EOS Data and Information System, EOSDIS) will be established to facilitate the archiving and analysis of raw, processed, and derived data products.

The combination of high spectral/low temporal resolution and low spectral/high temporal data provided by EOS surface imagers (High Resolution Imaging Spectrometer, HIRIS, Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER), Multi-Angle Imaging Spectra-Radiometer (MISR), and Moderate Resolution Imaging Spectrometer, MODIS) will supply several important variables required by ecosystem models (154). Rapid biophysical processes such as photosynthesis and evapotranspiration require data at daily if not diurnal intervals and at moderate resolution. MODIS will provide, at moderate resolutions (500 m), high temporal data that is currently provided at coarse spatial resolution (1–4 km) by NOAA's Advanced Very High Resolution Radiometer (AVHRR). Beyond its contributions to atmospheric calibrations, MISR will provide moderate resolution observations of multi-angle relectance properties of the surface. Applications of ASTER data will focus on high resolution measurements of land and water surface temperatures. Regional-scale variability of vegetation chemical quality is important for estimating decomposition rates and can be well represented by strategic sampling using HIRIS. Vegetation biochemistry important to decomposition is temporally less dynamic than biophysical processes. Sampling at two to three week intervals throughout the growing season and at time of senescence will be adequate to track seasonal dynamics that, when integrated over periods of years, will indicate chemical changes due to climate or rising CO_2. Techniques such as spectral mixture analysis, particularly suited to EOS' multiband image data sets, can provide a framework for systematically defining both large and small scale features in the image data.

CONCLUDING REMARKS

Advances in technology and integrative techniques are adding substantially to the scaling of ecological information from local to global systems. Remote sensing makes it possible to measure select variables at time and spatial scales consistent with our global interests. The link to geographic information systems and simulation models "animates" these data in a broader and more dynamic context. Use of these technologies is, however, predicated on the assumption that we recognize the appropriate variables to be scaled. Developments in theory and multiscaled, integrated measurement programs are necessary to provide the links to ground-based understanding. Approaches to extrapolation should consider the following:

1. *Stratified sampling procedures are required to address biospheric processes which vary in time and space.* The level of stratification will depend on the complexity of the process of interest and its response characteristics as the scale is changed. Accurate estimates of photosynthetic rates and conductances from vegetation indices, for example, will require stratification by biome type, at the very least, to account for conversion efficiencies and potential environmental limitations.
2. *Identification of controlling factors and the use of gradients sensible from space will enable regional extrapolations with remotely sensed data and will be amenable to simulation models.* Limiting or controlling factors will often govern variability in ecological processes. Remote observations can serve as state variables to drive rate calculations within models.
3. *Time-series of remote sensing data are central to studies in global change.* However, the utility of long-term data sets from current operational satellites is hindered by the lack of instrument calibrations to monitor changes in radiometric sensitivity over time. Future programs must consider this a priority.
4. *A hierarchy of spatial resolution measurements is required to address mesoscale heterogeneity if generalizations to global scales are to be successful.* Landscape and regional heterogeneity contribute significantly to the scaling properties of some processes and must be included in extrapolations. Remote sensing can be used to delineate habitats within

which process variation may be minimized. Moreover, characterization of sub-pixel variation for global-scale instruments such as AVHRR and MODIS is needed for scaling process measurements and calibrations.
5. *Global geographic data bases of parameters such as vegetation cover, land use, soil properties, etc will determine extrapolation and modeling capabilities at the global scale.* These data will be required at scales that reflect their effect on regional and global processes and which are relevant to modeling goals.
6. *Extrapolations of local to regional measurements must combine modeling at the process level, remote observations of biophysical and ecological characteristic relevant to landscape, regional and global dynamics, and synthesis with the aid of geographic information systems.*

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