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Simulating the climatic effects on vegetation: approaches, issues and challenges

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Abstract: Vegetation modelling has been viewed as a major approach for examining the dynamics of vegetation under climatic change. However, the characterization of uncertainty of model results is still a key issue. In order to improve future model-based research, it is important to synthesize the current approaches and the issues that arise in vegetation modelling and to propose potential strategies for improving model-based research. This study first reviews the progress of vegetation models from static-equilibrium to transient-dynamic and to current coupled multi-objective vegetation models. Then, the four main sources leading to the uncertainty of model results are described, including (1) factors related to vegetation models (their structure, assumption and parameterization), (2) the data used to run a model, (3) the approaches used to validate model results, and (4) the spatiotemporal scaling issues involved in vegetation modelling. Finally, four strategies are proposed for improving future model-based research. These include improvements in the model structure and parameterization, enhancement of the quality of analytical data, improvement of the analytical approaches, and continued development of coupled dynamic vegetation models. Using a literature synthesis, this study provides researchers with a general guidance on applying vegetation models for simulating the effects of climatic variations on terrestrial vegetation.

Key words: approach, challenge, climate change, issue, uncertainty, vegetation modelling.

I Introduction

The terrestrial biosphere and the atmosphere interact with each other through a variety of mechanisms that include the carbon, nitrogen and water cycles. Through these mechanisms, natural and human-induced climate change produces changes in terrestrial vegetation. Over the past decades, studies have confirmed climate-induced effects on vegetation, such as shifts in the environmental function of forests (eg, Hollister et al., 2005) and the changes of carbon cycles (eg, Berthelot et al., 2005). Moreover, additional studies have revealed that climate-induced changes in vegetation are ongoing (eg, Hinzman et al., 2005). Given that terrestrial vegetation is very important to human society and that it has a limited

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capacity to adapt to rapid climate change (e.g., Fischlin et al., 2007), simulating climatic effects on terrestrial vegetation becomes a paramount practical issue.

Terrestrial vegetation responds to climate change at different spatiotemporal scales. At the global scale, species evolution and migration due to climate change may take years to millennia. At the regional scale, changes in succession, competition and reproduction of vegetation require years to centuries. At the local scale, changes in the physiological processes of plants such as respiration rate take hours to seasons (e.g., Dale and Rauscher, 1994). From a biogeographical perspective, climate change can shift the distribution, structure and composition of terrestrial vegetation (Jackson and Overpeck, 2000; Koca et al., 2006). From a biophysical and biogeochemical perspective, climate change can trigger changes in the canopy height, biomass and leaf area index (LAI) of vegetation as well as the cycling of carbon and nitrogen in terrestrial vegetation. Climate change can also shift the regime of wildfires, thus further affecting terrestrial vegetation.

Because the mechanisms that trigger changes in vegetation are very complex, vegetation modelling has been viewed as a major tool for investigating the effects of climate change on vegetation (Bolliger et al., 2000; Schumacher et al., 2004). Vegetation models, either static-equilibrium or dynamic-transient, have utility in examining the climatic effects on vegetation because: (1) vegetation models can incorporate explicit representations of some of the mechanistic processes of vegetation, such as tree establishment, growth and death, and therefore are able to capture the response of vegetation to climate change (Cramer, 2002); (2) vegetation models can be applied at large spatial scales, which enables researchers to study the broad spatial patterns of vegetation (Prentice et al., 1996); (3) vegetation models can be updated or revised when new knowledge and techniques become available; and (4) vegetation modelling is often time-saving and less expensive compared to field observations.

Although vegetation models of differing sophistication have been developed to study climatic effects on terrestrial vegetation, the uncertainty of model results is still a key issue of concern to researchers. To improve model-based research, it is necessary to assess the major methods and issues in vegetation modelling and to propose strategies for promoting the quality of model results. However, few syntheses of the relevant literature have been done. The goals of this study are: (1) to summarize the vegetation modelling approaches for studying climatic effects on vegetation; (2) to analyse the major issues that lead to uncertainties in model results; and (3) to identify the challenges that arise in improving future model-related research.

II Simulating the climatic effects on terrestrial vegetation: approaches

1 Static-equilibrium vegetation models

Simulating the climate-induced biogeographical dynamics of vegetation was a main task for earlier generations of vegetation models. Correlations of control variables (such as climatic factors) and response variables (such as vegetation-type, biome or species distributions) have played a crucial role in predicting the response of vegetation to climate change (Burke et al., 1997). For example, the Holdridge diagram (Holdridge, 1947) used three bioclimatic variables, i.e., the biotemperature, mean annual precipitation and a ratio of potential evapotranspiration to mean annual precipitation, to express the relation of macroclimatic pattern and life zones on the Earth. Using the Holdridge classification schemes to estimate climatic effects on vegetation assumes that the distribution of vegetation is solely correlated to climate, and the climate-induced shift of vegetation occurs as a fixed unit (as opposed to individualistic responses of the component species in a vegetation type). Later, the Box model
(Box, 1981) was developed to organize plant species on the Earth into characteristic plant functional types (PFTs) based on their physiognomic and morphological traits and their relation to macroclimate. The geographical space of a PFT is then defined by its climatic limits, and a particular, usually global, climatic data set.

Like the Holdridge classification scheme and the Box model, statistical approaches such as climate response surfaces (eg, Huntley et al., 1995), regression models (eg, Smith and Shugart, 1993; Calef et al., 2005) and probabilistic models (eg, Siegel et al., 1995) were used to predict the climate-induced changes in the distribution and habitat of natural vegetation. These approaches still assumed that the macroclimate is the major factor determining the features of vegetation distribution at regional or global scales. For example, climate-pollen response surfaces (eg, Overpeck et al., 1991) have been coupled with climate-model output to project climatic effects on the distribution of terrestrial vegetation. Similarly, probabilistic models or presence-absence response surfaces (eg, Siegel et al., 1995; Shafer et al., 2001) utilized species or ecosystem distributions and climate data to estimate the probability of occurrence of those ecosystems or species under given climatic conditions.

Because vegetation models built on statistical relations between vegetation distribution and macroclimate cannot determine or distinguish the particular mechanisms that may drive the spatial shift of vegetation (Neilson et al., 1992), researchers have constructed rule- and ecophysiology-based models. Rule-based models such as the CCVM (Lenihan and Neilson, 1993) used a set of rules (expressed as climate limits, much like the Box model) to specify the distribution of vegetation. For example, minimum temperature and evapotranspiration were used to constrain the distribution of different life forms. Ecophysiology-based models such as BIOME (Prentice et al., 1992) aimed at understanding the fundamental aspects of structure in terrestrial ecosystems. In these models, terrestrial vegetation was grouped into several different PFTs based on a set of climatic tolerances. Differing from simple bioclimatic classification schemes, the climate limits of each PFT in ecophysiology-based models are expressed in terms of fundamental phenological constraints rather than observed correlations between the macroclimate and vegetation distribution.

The current equilibrium vegetation models incorporate more mechanistic processes of plants, and consider more the interactions between the biosphere and the atmosphere. For example, BIOME4 (Kaplan et al., 2002; 2003) is a typical example of equilibrium vegetation models. Like the ecophysiology-based models, BIOME4 still simulates the distribution of vegetation in the form of PFTs but with significant improvements, including improved parameterization of the PFTs. In BIOME4, each PFT is assigned a set of bioclimatic limits, which determine whether it will be simulated to exist in a grid cell. Moreover, BIOME4 contains a coupled carbon and water flux scheme, which determines the seasonal maximum LAI based on a daily timestep simulation of the soil water balance and monthly calculations of canopy conductance, photosynthesis and respiration (Haxeltine and Prentice, 1996; Kaplan et al., 2002). Compared to the rule- and ecophysiology-based models, current equilibrium vegetation models can more accurately simulate the distribution and the biogeochemical dynamics of terrestrial vegetation under climatic change.

2 Dynamic-transient vegetation models

In fact, vegetation is far from an equilibrium system. In 1926, Cooper (1926) viewed vegetation dynamics as a ‘flowing stream’. Because static vegetation models cannot capture non-linear or threshold effects along the trajectory of vegetation change, including interannual variations, dynamic vegetation models were developed to complement static vegetation models, to simulate vegetation...
dynamics such as the succession of plants through time, and to estimate the variability of the terrestrial carbon and nitrogen and their responses to episodic events such as drought and fire (Tian et al., 1998; Bachelet et al., 2001). To some degree, dynamic vegetation models fall into four subcategories: (1) models simulating the species composition and distribution of vegetation; (2) models focusing on the biogeochemical processes of vegetation; (3) models addressing the physiological processes of vegetation; and (4) coupled dynamic multifunctional models that incorporate all or some of the ecological, biogeochemical and physiological variations. Dynamic models often have an ability to predict the responses of vegetation to climate change at timescales ranging from days to centuries, and at spatial scales ranging from local to global (Woodward and Lomas, 2004).

Dynamic models can be constructed by coupling static models with smaller scale ecosystems or species models. Because both ecosystems and species models are capable of simulating vegetation and species change by considering the differential birth, growth and death of individual trees as a function of species' response to climatic factors, light and nutrients, the resulting dynamic models are therefore able to simulate transient changes in vegetation distribution. For example, Steffen et al. (1996) developed a dynamic global vegetation model (DGVM) to simulate the transient changes in vegetation distribution over a decadal timescale. The structure of this DGVM is based on a linkage between an equilibrium global vegetation model and smaller-scale ecosystem dynamic modules that simulate the rate of vegetation change.

Physiological models simulate the physiological processes of vegetation such as stomatal resistance and plant transpiration. In these models, the transpiration rates of plants are linked to their photosynthesis via stomatal conductance or leaf area (Running et al., 1989). When physiological models are linked to other models such as demographic vegetation models or ecosystem models, they have an ability to simulate the succession, competition and other ecological processes of plants under climate change. For example, small-scale ecosystem models have an ability to estimate the gas exchange processes such as photosynthesis, respiration and evapotranspiration (eg, Kergoat et al., 2002).

Biogeochemical models aim to predict the carbon and nitrogen cycle in terrestrial vegetation. For example, a set of carbon cycle models (eg, King et al., 1997; Ito and Oikawa; 2002) were used to examine the carbon dynamics in terrestrial ecosystems under climatic change. In such models, terrestrial carbon storage is divided into different compartments such as foliage, stem, root, litter and mineral soil. The division of carbon into different compartments allows researchers to understand the carbon fluxes in the biosphere. These models estimate net primary production (NPP) and net ecosystem production (NEP) by explicitly calculating such carbon fluxes as gross primary production (GPP), plant respiration and soil decomposition on a monthly timestep. These fluxes are regulated by a multitude of environmental factors at the physiological scale. In addition, empirical models based on the normalized difference vegetation index (NDVI) and climate variables can be used to analyse the response of terrestrial productivity to climate change (eg, Potter et al., 1999; Zhang et al., 2003).

Current dynamic vegetation models are mostly multifunctional and combine process-based, large-scale representations of terrestrial vegetation dynamics and the exchanges of carbon and water between the biosphere and the atmosphere (for these reasons, they are referred to as DGVMs – dynamic global vegetation models). The Lund-Potsdam-Jena (LPJ) DGVM (Sitch et al., 2003) is a typical example. In LPJ, the PFTs are differentiated by their physiological, morphological, phenological,
bioclimatic and fire-response attributes. LPJ incorporates some of the principal processes of the biosphere that influence the global carbon cycle (eg, photosynthesis, autotrophic and heterotrophic respiration of plants and in soils) and the latent, sensible and kinetic energy exchanges at the surface of soils and plants. LPJ also considers competitive processes between PFTs, such as light competition and sapling establishment. The carbon, water and nitrogen flows are simulated on a daily basis, while vegetation structure, PFT population densities and NPP of each PFT are updated monthly and annually. Most current dynamic models can be coupled with climate or other land-cover models and are able to simulate transient changes in vegetation distribution, structure and function, and the terrestrial carbon and nitrogen cycle under climatic change (Zaehle et al., 2005; Cowling and Shin, 2006).

III Simulating the climatic effects on terrestrial vegetation: issues

1 Issues related to vegetation models

The structure of vegetation models affects model results in three ways. First, the bioclimatic classification models usually predict the distribution of high-level physiognomic units such as biomes and life zones at the broad spatial scale but ignore the individualistic response of species to climate change (Peng, 2000). Consequently, the equilibrium character of the bioclimatic relationships limits the applications of such models to long-term scenarios of changing climate (Kirilenko and Solomon, 1998). Static models may ignore migration or succession processes of terrestrial vegetation, which further limits their ability to simulate the transient dynamics of terrestrial vegetation (Prentice and Solomon, 1990). Likewise, if dynamic models do not stress the structure difference among different types of vegetation, their ability to simulate the categories and distribution of terrestrial vegetation is limited. In addition, the simulations of the biochemical dynamics such as the carbon and nitrogen cycles are mostly based on fixed vegetation types (Walker, 1994) and the simulations of natural disturbances (eg, wildfire) or human disturbance (eg, land-use change) may not be adequate in both static and dynamic models (eg, Thonicke et al., 2001).

Second, vegetation model results are affected by assumptions and theoretical foundations. Static models mostly assume that climate is the primary factor for controlling vegetation dynamics. The resilience of terrestrial vegetation under external environmental alterations and other important factors such as human activities that affect the vegetation dynamic are ignored (Loehle and LeBlanc, 1996). However, other disturbances such as wildfire, grazing and deforestation can be the dominant factors controlling the distribution of terrestrial vegetation in a given area. Therefore, vegetation models that take into account only climatic factors may not accurately simulate the spatio-temporal dynamics of terrestrial vegetation under climate change (Camill, 2000), largely because the implicit cause-effect relationship in vegetation models may be problematic (Scheffer et al., 2005). In addition, the aggregation of all species into several PFTs that may encompass the full spectrum of migration rates hinders the accuracy of model results (Neilson et al., 2005).

Third, the parameterization of physiological, biological and biogeochemical processes of terrestrial vegetation is still difficult because of our limited knowledge of plant physiology and biology, the limitation of sampling and the key processes which may be currently unknown (Grieb et al., 1999; Mitchell and Csillag, 2001). For example, Arora and Boer (2005) pointed out that leaf phenology remains one of the most difficult processes to parameterize in vegetation models because of our incomplete understanding of leaf onset and senescence. In addition, information with considerable uncertainty may continue to be used to parameterize future vegetation models (Gifford, 2003). The selection and
use of static parameters (e.g., leaf nitrogen concentration) in vegetation models is likely to affect model results by overestimating the respiration of plants and subsequently underestimating the productivity estimates (Wythers et al., 2005).

2 Issues related to analytical data
The outputs from vegetation models are often hampered by considerable uncertainties associated with the input data used to run a model (Kickert et al., 1999). Problems with the input data include missing key components, errors associated with biased or incomplete observations, and the resolution of the data. For example, climate data from general circulation models (GCMs) may be biased because of the uncertainties in future greenhouse gases and aerosol emissions, radiative forcings, global and regional climate sensitivity (Forest et al., 2002; Stott and Kettleborough, 2002) and the cycle of carbon (Lenton and Huntingford, 2003) specified in GCMs. In addition, the uncertainties related to future population growth, technological progress, economic activity, land-use and land-cover changes, and the simplification of the complex physical processes that govern climate in GCMs can affect the accuracy and reliability of GCM data (Loehle and LeBlanc, 1996), which in turn affects vegetation modelling being run using such GCM data (Jones, 2000).

Satellite-based land- and tree-cover data are increasingly used to evaluate a model’s ability to simulate terrestrial vegetation. However, human-induced errors in satellite-image processing such as image classification may bias the realistic distribution pattern of vegetation in an area (Campbell, 2002). Therefore, satellite-based land-cover data used to validate model results may greatly influence the accuracy assessment of model results. In addition, lack of data that would help to make vegetation models mechanistic and to provide evidence on what climate-induced impacts will occur is one of the critical gaps in developing dynamic models and in validating model results (Tian et al., 1998). For example, Neilson et al. (2005) pointed out that theories about climate change and migration of vegetation are limited by inadequate data for key processes at the different spatiotemporal scales. The spatial resolution of input data affects model results. Turner et al. (1996) pointed out that the model simulations run by coarser input data is more likely to bias the resulting estimates of vegetation dynamics than those run by finer input data.

3 Issues related to analytical approaches
Categorical-data comparison approaches are used to assess the accuracy of model results through comparing simulated and observed distributions of vegetation type. Statistics, such as the Kappa statistic (Congalton and Green, 1999), Kappa-for-location (Pontius, 2000) and Fuzzy Kappa (Hagen, 2003) have strengths and weaknesses in assessing a model’s accuracy. For example, the Kappa statistic lacks the ability to measure error magnitude (Congalton, 1991; Foody, 2002) and tends to underestimate the overall similarity between simulated and observed spatial pattern of terrestrial vegetation (Foody, 1992). The Fuzzy Kappa can underestimate a model’s ability by overestimating the expected similarity between two compared data sets (Hagen, 2003). The receiver (or relative) operating characteristic (ROC) technique is sensitive to the number of vegetation types in the two data sets being compared (Fielding and Bell, 1997; Pontius and Schneider, 2001).

Continuous-data comparison approaches assess a model’s ability to simulate the state of ecological variables that are numerical. Statistics, such as confidence levels (Barrett et al., 2001), correlation and regression coefficients, Kendall’s tau and measures of absolute and relative error (Gordon et al., 2004) are widely used in model comparison and evaluation research. However, they
may be problematic in some cases. For example, the correlation coefficient cannot determine whether two patterns have the same amplitude of variation (Taylor, 2001). The correlation coefficient is sensitive to influential data and outliers from two compared simulations but insensitive in situations when the compared data differ by a constant factor (Murphy and Epstein, 1989; Storch and Zwiers, 1999). Similarly, root-mean-squared error is very sensitive to systematic errors because the penalty grows as the square of the error (Storch and Zwiers, 1999). In addition, most statistics assume that the data being compared are independent of one another. However, model results are often spatiotemporally autocorrelated.

4 Issues related to spatiotemporal scaling

The spatiotemporal scaling in vegetation modelling may greatly affect the model results. For example, the mismatch between the coarser spatial resolution of GCM data and the relatively finer resolution of vegetation models has long been a concern in vegetation modelling (Adams et al., 2003). In addition, modelling interactions between land-use change and vegetation dynamics is still a challenge because vegetation models often rely on pixel sizes of a few kilometres or more but the land-use change frequently occurs on a much smaller scale (Peng, 2000), which makes the interactions among land-use drivers, topography and climate change difficult to simulate.

The ‘scaling-up’ approaches used in vegetation modelling to extrapolate information from individuals to ecosystems, or from sites to regions to the globe, are often based on observations, experiments and modelling of individuals or sites. However, the basic assumptions of environmental homogeneity across different spatial scales are questionable (Tian et al., 1998; Liu et al., 2006). Likewise, the ‘scaling-down’ approaches that apply the relation of large-scale patterns of vegetation and climate to local and landscape scales may ignore the fact that other processes rather than climate may play important roles in vegetation dynamics at local scales (Moorcroft et al., 2001).

IV Simulating the climatic effects on terrestrial vegetation: challenges

1 To improve the model design and parameterization

Because vegetation modelling often involves a variety of processes of plants, such as the water and carbon cycles in the soil-vegetation-atmosphere system, and because the intent of a vegetation model may vary in practical applications, establishing a model with a clear structural hierarchy would allow researchers easily to alter and compare the individual equations and to select the level of model detail based on the availability of data or the particular research question being investigated (Homann et al., 2000). Given that static models may ignore the biogeochemical processes of plants, it would be rewarding to couple them with biogeochemical models to address the effects of climate change on vegetation. Similarly, if dynamic models do not consider competition between plants and instead determine the existence and fractional coverage of vegetation based on inferred climate-vegetation relationships, then it would be desirable to include the mechanisms of competition for light and water among different PFTs (Daly et al., 2000; Arora and Boer, 2006). In addition, both static and dynamic models need to incorporate the impacts of land-cover change on vegetation (Bond-Lamberty et al., 2005) and the coupling of climate and carbon cycle models should be improved to better represent the photosynthesis process of plants (Matthews et al., 2005).

Second, vegetation models should be developed to incorporate as many factors as possible that have a big role in changing the vegetation’s structure and function and the cycles of carbon and nitrogen in terrestrial ecosystems. Van Minnen et al. (2000) suggested that the ability of plant species
to migrate is one of the critical issues for accurately assessing future responses of terrestrial vegetation to climate change. Given that natural disturbances (eg, forest fire and insects) and human activities (eg, land use and grazing) are critical factors in determining the composition, structure and dynamics of most vegetation (Thonicke et al., 2001), new vegetation models should have an ability to simulate the role of these factors on vegetation dynamics (Peng, 2000). For example, better estimates of carbon sources and sinks require improved assessments of current and future deforestation (Cramer et al., 2004) and the role of land-cover changes in changing the cycles of terrestrial carbon and nitrogen (Chen et al., 2006).

Third, it is very important to determine which processes and parameters contribute most to the uncertainty of model results (Knorr and Heimann, 2001a; 2001b; Mitchell and Csillag, 2001). For example, Peters (2002) argued that our limited understanding of the key processes in many ecotones hinders the reliability of model results. The uncertainty in the simulation of PFT distributions and in the estimates of the carbon cycle mainly result from the uncertainty in parameters controlling the photosynthesis, evapotranspiration and root distribution of plants and the water balance (Hallgren and Pitman, 2000; Zaehele et al., 2005). Therefore, efforts must be made to determine which parameters need further attention in observational work and in their representation in models (Matthews et al., 2005). For those parameter uncertainties caused by limited sampling, much work on sampling and corresponding statistical analysis is needed (Higgins et al., 2003).

2. To improve the quality of model-driven and validation data
The reliability of model results highly depends on the quality of climate data used to run a model (Kickert et al., 1999). To simulate accurately the effects of climatic variations on vegetation requires input climate data to capture those aspects of climate that control ecological processes, including key spatial gradients and modes of temporal variability (Kittel et al., 2004). Therefore, it is necessary to further the study of climate projection and the positive feedbacks between the terrestrial carbon cycle and climate (Matthews et al., 2005; Meir et al., 2006). Meanwhile, more efforts should be made in studying the frequency, intensity and magnitude of extreme weather events, and how they affect terrestrial vegetation. In addition, because one of the major uncertainties in vegetation modelling is in understanding processes in soil-vegetation-atmosphere systems, continuous, long-term data are therefore needed to model correctly the balances of water, energy and CO₂ in these systems (Halldin et al., 1999; Lundin et al., 1999).

The quality of other data is also important for the accuracy and evaluation of model results (Pan et al., 1996). Long time-series data or experiments allow researchers to understand better the relative magnitudes of short- and long-term responses of vegetation under climate change (Hanson et al., 2005). In addition, more and continuing field observations are needed at sites where studies have already been conducted in order to calibrate the model results (Higgins et al., 2003). In order to make full use of vegetation models, it is necessary to establish the magnitude and sources of uncertainty associated with data, which will be useful for guiding field surveys and experiments (Grieb et al., 1999).

3. To improve the model evaluation and the uncertainty analysis
Vegetation models must be tested for their ability to reproduce features of real vegetation (Hickler et al., 2004). Model evaluation allows researchers to determine the accuracy and applicability of a model (Bolliger et al., 2000). However, because model evaluation is probably sensitive to the selection of the evaluation methods, the evaluation strategy needs to be prescribed to solve such sensitivity
issues. In addition, model evaluation should be closely related to its intended purpose: description, understanding and prediction (Araujo and Guisan, 2006). Intercomparisons of results from different models should be stressed because they are very important with regard to improving our understanding of the model behavior, assessing the robustness of inferred mechanisms used to build a model, and measuring the stability of selected variables (Bolliger et al., 2000; Knorr and Heimann, 2001a; 2001b).

The promotion of approaches for evaluating model results is important. The statistical confidence levels (Barrett et al., 2001), Markov chain (Schulz et al., 2001) and Monte Carlo-based uncertainty estimation (Peltoniemi et al., 2006), Bayesian probabilities (Webster and Sokolov, 2000; Katz, 2002) and statements of uncertainty such as probability density functions (Grieb et al., 1999; Radtke et al., 2001) allow us to weigh the analytical results and to estimate the predictive uncertainty of the response of vegetation dynamics to climate change. Nevertheless, innovative methods for evaluating model results and for exploring parameter uncertainty in complex vegetation models are still needed. Different approaches for model evaluation and uncertainty analysis can complement each other and thus provide more insights into the contribution of various factors to the uncertainty of model results (House et al., 2003).

4 To strengthen the development of coupled dynamic vegetation models

Vegetation models are developed at different levels of biological organization: global, regional or landscape, community and individual plants (Dale and Rauscher, 1994). However, no model can address all aspects of vegetation dynamics at different spatial scales. Moreover, the biosphere and the atmosphere are a coupled system with biogeophysical and biogeochemical processes occurring across a range of timescales, ranging from short (ie, seconds to hours) to intermediate (ie, days to months) and to longer (eg, seasons, years and decades) (Foley et al., 2000). On different timescales, the processes that control the exchange of matter and energy between the biosphere and the atmosphere are different. In order to consider the full range of coupled atmosphere-biosphere processes, vegetation models should include short, intermediate and long-term ecological phenomena occurring at different spatial scales, which necessitates coupling different vegetation models or coupling vegetation models with other land-use and climate models.

Scale is an important issue in simulating climatic effects on vegetation (Higgins and Vellinga, 2004) and has been a critical impediment to incorporating important fine-scale processes into large-scale vegetation models (Moorcroft et al., 2001). Our knowledge of fine-scale physiological and ecological processes comes from a variety of measurements and experiments made at spatial resolutions considerably smaller than the large scale at which many vegetation models are defined. However, it is the interactions of factors and processes at different scales that determine the vegetation dynamics. Therefore, new vegetation models should have an ability to quantify the mechanisms from micro-level fast ecophysiological responses to macro-level slow acclimation in the pattern, structure and function of vegetation (Cao et al., 2005). Integrating approaches of different vegetation models is therefore necessary because they can help us to understand the interconnections and interactions among different mechanisms at different scales. Given that the role of local-scale effects is poorly explored, new integrated vegetation models need to stress fine-scale processes such as species dispersal (del Barrio et al., 2006).

V Conclusions

Vegetation models have progressed from static-equilibrium to transient-dynamic models. The former simulates vegetation
dynamics primarily as a function of the abiotic biophysical environment. Because the data used to infer the abiotic environment are from large spatial scales, these vegetation models are considered a top-down approach in vegetation modelling. In contrast, the latter simulates vegetation dynamics based on some mechanistic processes of terrestrial vegetation. Because local-scale or species-specific information is often used to describe the mechanistic processes of plants, these vegetation models are considered a bottom-up approach. In comparing the two, dynamic models are superior in simulating climatic effects on vegetation because they can include many mechanistic processes of plants and incorporate more non-climatic factors.

The factors that affect the accuracy of model results are manifold. First, the structure, assumptions and parameterization of a model each influence the model results. Static models often ignore some mechanistic processes of vegetation. In contrast, dynamic models may overlook the structural differences among PFTs. A model’s assumptions may overemphasize the roles of some factors but overlook other factors that are important in controlling vegetation dynamics. The parameterization of some key process of plants is a key issue in vegetation modelling; second, the quality of data used to run a model and to assess model results greatly affects the accuracy of model results; third, both categorical- and continuous-data comparison approaches have their own weaknesses and thus may bias the accuracy assessment of model results; and, fourth, the mismatch of the spatiotemporal resolution of data used in vegetation modelling and the extrapolation of information from one scale to another greatly influence the accuracy of model results.

To address the major factors resulting in the uncertainty of model results, more attention should be directed towards: (1) establishing structural models with a good hierarchy that can incorporate as many factors as possible in affecting the vegetation’s structure and function and the cycles of carbon and nitrogen in terrestrial vegetation; (2) improving the quality of model input and validation data, especially high-quality input climate data and field observations needed to calibrate model results; (3) strengthening the intercomparison between different model results, the validation of model results by multiple approaches and the development of new methods for evaluating model results; and (4) promoting the coupling of different vegetation models or vegetation models with climate or land-cover models, which will greatly contribute to our understanding of the mechanisms from micro-level fast response to macro-level slow acclimation of vegetation to climate change.

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