Approaches to Incorporating Climate Change Effects in State and Transition Simulation Models of Vegetation

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Abstract

Understanding landscape vegetation dynamics often involves the use of scientifically-based modeling tools that are capable of testing alternative management scenarios given complex ecological, management, and social conditions. State-and-transition simulation model (STSM) frameworks and software such as PATH and VDDT are commonly used tools that simulate how landscapes might look and function in the future. Until recently, however, STSMs did not explicitly include climate change considerations. Yet the structure of STSMs makes them highly conducive to the incorporation of any probabilistic phenomenon. The central task in making a STSM climate-sensitive is describing the relevant processes in terms of probabilistic transitions. We discuss four different approaches we have implemented to inform climate-induced changes in vegetation and disturbance probabilities in STSMs using the dynamic global vegetation model MC1. These approaches are based on our work in several landscapes in the western United States using different modeling frameworks. Developing STSMs that consider future climate change will greatly broaden their utility, allowing managers and others to explore the roles of various processes and agents of change in landscape-level vegetation dynamics. However, numerous caveats exist. Regardless of how STSMs are made climate-sensitive, they neither simulate plant physiological responses directly nor predict landscape states by simulating landscape processes mechanistically. They are empirical models that reflect the current understanding of system properties and processes, help organize state-of-the-art knowledge and information, and serve as tools for quickly assessing the potential ramifications of management strategies. As such, they highlight the need for new research, while providing projections based on the best available information.

Keywords: climate change, coupled models, dynamic global vegetation models, state-and-transition simulation model, vegetation dynamics.

Introduction

Across the globe, plant communities are already experiencing the effects of climate change: warmer temperatures, earlier springs and earlier snowmelt, reduced snowpack, changes in fire regimes, and higher concentrations of CO_2 (Parry et al. 2007). There is increasingly strong evidence that climate change will profoundly alter vegetation structure and composition, ecosystem processes, and the future delivery of ecosystem goods and services (Parry et al. 2007). Coupling climate change projections with landscape vegetation dynamics is a promising approach that involves the use of scientifically based modeling tools that are capable of testing alternative management scenarios given complex ecological, management, and social conditions. State and transition simulation models (STSMs) are one tool for simulating how landscapes might look and function in the future and thus guide decisionmaking (Daniel and Frid 2012). With vegetation STSMs, different potential vegetation types are grouped into discrete state classes. Transitions from one state class to another may occur probabilistically or are empirically based; regardless, they represent the effects of ecological processes such as succession and wildfire and management actions (Daniel and Frid 2012). Although factors such as drought and frost kill have been included as probabilistic disturbances within STSMs (e.g., Evers et al. 2011), up until recently most STSMs did not include climate change considerations. Incorporating the effects of future climate change would increase the utility of STSMs as a common platform to collectively define the roles of various processes in projecting landscape-level vegetation dynamics. To the best of our knowledge, there are only a handful of studies where changing climate has been explicitly being incorporated into STSMs (e.g., Costanza et al. 2010, Hemstrom et al. in press, Provencher et al. 2009, Provencher and Anderson 2011, Yospin 2012).

Climate change can affect vegetation by altering the future abiotic and biotic conditions under which plant species establish, survive, reproduce and spread. Increased temperature, longer growing seasons, less snow, and more frequent drought conditions may increase plant stress and decrease a species' ability to survive in the drier and warmer parts of its range (Allen and Breshears 1998, Allen et al. 2010). Changes in abiotic conditions and subsequent effects on individual species reproduction, establishment and growth may in turn substantially alter plant competitive dynamics (Pfeifer-Meister et al. 2008). Rising CO_2 concentrations will also directly affect plant growth and productivity through a variety of mechanisms (Nowak et al. 2004). But climate change modifications of disturbance regimes, such as wildfire and insect and disease outbreaks, might be the most important factors for forcing future vegetation responses (Brown and Westerling 2004, Taylor and Beatty 2005, Westerling et al. 2006, Raffa et al. 2008, Pennisis 2009). Therefore, STSMs that consider changes in successional trajectories and disturbance regimes in response to changing climate are needed.

Considerations for Creating Climate-Sensitive State and Transition Simulation Models

The structure of STSMs makes them highly conducive to the incorporation of any probabilistic phenomenon using information generated from another source, dataset, modeling framework, or even expert knowledge (Daniel and Frid 2012). The central task in making a STSM climate-sensitive is describing the relevant processes in terms of new assumptions and empirical relationships, including probabilistic transitions. This can be a challenge because it is not always clear how information from general circulation models (GCMs) and climate-sensitive vegetation models can be reduced to a set of empirical relationships, particularly to the fine spatial grain and level of detail at which many STSMs are typically developed. Information regarding potential future climate changes can be generated by more than twenty different GCMs that give variable projections of future climate (Littell et al. 2011). However, GCMs are highly complex mechanistic models that estimate potential future climatic trends on grids at resolutions of thousands or tens of thousands of square kilometers. Each grid-cell represents average conditions within its boundaries, producing daily to yearly estimates of a variety of climate attributes. Because GCMs estimate potential future climatic trends using coarse spatial grids, they are frequently spatially downscaled using a variety of quantitative techniques (Littell et al. 2011). General circulation models are all ‘‘forced’’ with scenarios of greenhouse gas emissions that reflect different assumptions about future global economic activity and fossil fuel use (Nakicenovic et al. 2000). Thus a single emission scenario can generate multiple future climate scenarios using different GCMs. Alternately, a single GCM can project multiple future scenarios under different emissions scenarios. Ideally, output from multiple GCMs and emission scenarios would be used for input into a climate-sensitive vegetation model to capture the available range of future conditions and simulate their consequences for ecosystems. However, this ensemble approach is computationally intensive (Littell et al. 2011) and furthermore requires that all climate variables needed to run the vegetation model are readily available. One approach to avoid this problem is to pair scenarios based on a gradient of risk (Kerns et al. 2009, Littell et al. 2011, Mote and Salathé 2010). For example, one could pair a scenario combination (GCM and emission scenario) at two extremes (e.g., less warming vs. lots of warming; precipitation increases vs. precipitation decreases). However, the risk framework may only be specific to a single resource issue. That is, a high risk scenario for potential changes in wildfire may be different than a high risk scenario for potential changes in an endangered species habitat.

Downscaled future climate data are becoming increasingly available at scales useful for land managers (e.g., 0.6 km^2, Rogers et al. 2011). However, it is important to assess whether downscaling has exceeded the resolution supported by observations, recognizing that finer-scale projections are not always more reliable (Littell et al. 2011). Moreover, climate change data alone are not usually useful input data for a STSM. Climate data can be used to develop the empirical relationships required to modify STSM transition probabilities (e.g., fire frequencies, insect and disease outbreaks, changes in tree growth rates) for projecting changes in potential vegetation, or as input into other models that explicitly incorporate climate information and produce output that can then be used by STSMs. Provencher and Anderson (2011) used projections of future CO_2, precipitation and temperature, to create trends in STSM disturbance transition probabilities. The authors also used information about species regeneration and simulated range shifts from the literature to develop a series of hypothetical range shifts for vegetation in Nevada. Costanza et al. (2010) modeled the effects of climate change by altering fire frequencies using the spatially explicit TELSA model (Kurz et al. 2000). Historic (1979–2010) climate and fire occurrence data were used to hindcast relationships between the acres burned and climate variables (i.e., temperature and precipitation). Those relationships were then incorporated as a multiplier on fire transition probabilities in the TELSA model runs. A statistical approach may be one method for generating projections, but may miss the important interactions between climate, disturbance, and succession that will drive changes in vegetation over the coming century.

A commonly used approach for landscape analysis is to stratify the landscape according to one or more criteria that are considered to be important external drivers of vegetation change, and then to develop a separate pathway diagram (STSM) for each stratum (the spatially stratified state-and-transition simulation model approach, Daniel and Frid 2012). Biophysical drivers, such as soils, climate, and topography are typically used to define a stratum, based on existing ecological classification systems, such as potential vegetation types (PVTs) (Chiarucci et al. 2010) or biophysical settings (Long et al. 2006). However, modelers assume that the landscape stratification is then fixed over planning horizons of several decades or centuries, although strata can move through numerous state classes according to the defined STSM transition pathways. But the assumption that the present-day landscape stratification will remain constant over time is only valid if the underlying site conditions that define the stratum boundaries on the landscape remain constant. Because this is unlikely with future climate change, climate-sensitive models must by definition incorporate many spatially-stratified STSMs with transition pathways between strata. For example, such a model would allow transitions from a broadleaf forest PVT to a mixed conifer forest PVT and in turn to a conifer forest PVT. Others have operationally referred to such STSMs as a “mega-model” (i.e., Hemstrom et al. in press). Likewise, we will refer to these large spatially stratified STSMs with transition pathways between strata as mega-STSMs.

A number of climate-sensitive vegetation models are available that can be used to create climate sensitive STSMs. These models are either empirical and typically species-specific (e.g., Rehfeldt et al. 2006, 2008; Iverson et al. 2008), or mechanistic (i.e., process-based, or physical) (Keane et al. 2004) and usually not species-specific (e.g., Bugmann 2001, Bachelet et al. 2003). Empirical models fit parameters to observations and use statistical methods to make projections. By contrast, mechanistic models typically try to represent underlying physiological processes, and thus can incorporate complex and novel interactions. The capacity to include novel interactions allows a model to yield unexpected outcomes, which is a critical consideration for planning across a wide range of potential future conditions. However, mechanistic models are highly complex and require extensive training to use them correctly. They typically cannot incorporate the current vegetation as an initial starting condition (i.e., they require an extensive 'spin-up' period), cannot directly incorporate management, and produce outputs as plant physiognomic types instead of actual species. Thus, these models provide a fairly abstract view of potential vegetation in a landscape under a set of climatic conditions. Incorporating output from mechanistic models into STSMs would better allow their results to be used for management purposes.

Using MC1 to Build Climate Sensitive State-and-Transition Simulation Models

In the following section we present challenges and four approaches for incorporating climate-induced vegetation changes in STSMs using the dynamic global vegetation model MC1: (1) modifying potential vegetation using annual probabilities and transition multipliers calculated from MC1; (2) modifying potential vegetation by developing spatially explicit changes in vegetation using regression equations between MC1 output variables and site index and the Forest Vegetation Simulator (FVS); (3) modifying wildfire probabilities using annual probabilities and transition multipliers calculated from MC1; and (4) using MC1 output to develop a simple spatially-explicit rule-base to attenuate growth potential across a landscape. These approaches are based on our collaborative work across several landscapes in the western United States (Hemstrom et al. in press, Yospin 2012) using different modeling frameworks, and described in more detail in the following section.

Dynamic global vegetation models (DGVMs) use climate projections from GCMs to simulate vegetation potential, vegetation growth, carbon and nutrient dynamics, and some natural disturbance regimes (e.g., wildfire) at relatively coarse resolution (Bachelet et al. 2003). Output is usually at a coarser spatial grain than that at which land managers make decisions. Furthermore, DGVMs do not usually include species-specific information, detailed vegetation dynamics such as seed dispersal, fire adaptations of various species, or the effects that various land management activities might have on vegetation dynamics. MC1 is a DGVM that simulates plant type mixtures and broad vegetation types; pools and fluxes of carbon, nitrogen, and water through ecosystems; and fire disturbance. MC1 routinely generates century-long, regional-scale simulations on relatively coarse-scale data grids (Bachelet et al. 2003, 2005; Lenihan et al. 2008).

MC1 (Bachelet et al. 2001) is a good candidate for incorporating climate-induced vegetation changes in STSMs because the model is mechanistic, incorporates disturbance dynamics, and projects future vegetation mechanistically based on changes in climate and biogeochemistry. MC1 combines a biogeography model (MAPSS), a model to simulate fire disturbance (MC-FIRE), and a biogeochemistry model (Century). Therefore MC1 can provide relevant output about future changes in potential vegetation and wildfire regimes that can in turn can be used to alter site potential and wildfire probabilities in a connected suite of STSMs that make up a landscape.

Although MC1 produces projections of future changes in vegetation, it does so by predicting the life form or plant functional types mixtures, which are then classified into potential vegetation classes. A common challenge for using output from DGVMs such as MC1 is that these classes are not directly comparable to most locally defined STSM strata such as PVTs (fig. 1, table 1). Thus a key methodological issue in using MC1 output to build a climate-sensitive STSM is how to relate or "cross-walk" the local strata within a study area, such as a PVTs, to the more broadly defined potential vegetation classes simulated by MC1. Typically MC1 potential vegetation classes combine numerous species and structural conditions into single entities (table 1). For example, "temperate needleleaf forest" is an important MC1 potential vegetation class simulated for many western U.S. forested landscapes. In the interior Pacific Northwest, this broad class would correspond to a variety of strata, including ponderosa pine, lodgepole pine, Douglas-fir, and grand fir. Because most STSM PVTs

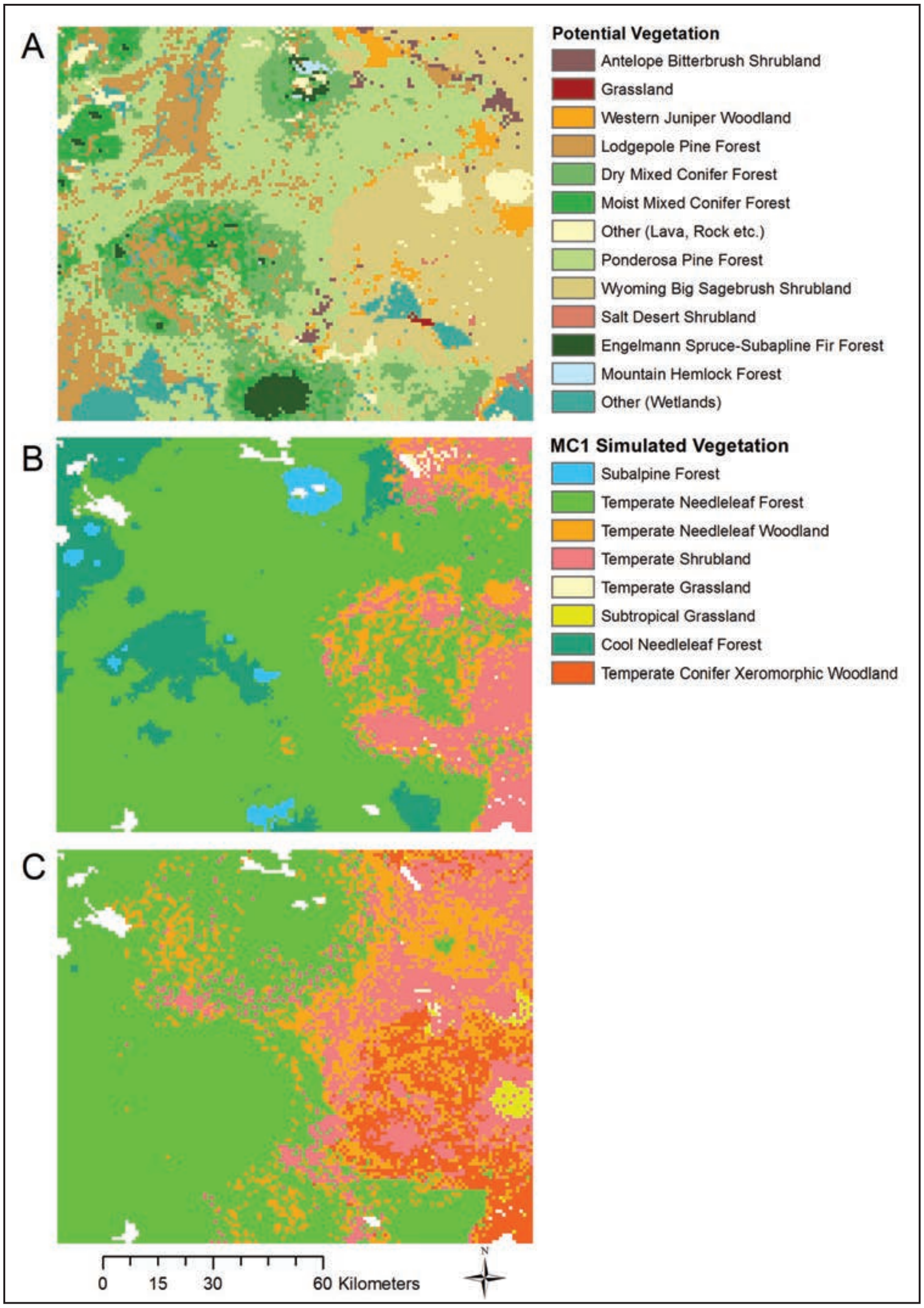

Figure 1—Model output for vegetation types in a central Oregon area (30-arc sec grid, 800-m^2): (A) STSM potential vegetation types generated from imputed data (B) MC1 potential vegetation classes projected for the historical period (30-year mode vegetation), and (C) MC1 potential vegetation classes projected for the last part of the 21st century (30-year mode vegetation, MIRCO A2 scenario).

currently in use represent relatively fine-scale ecological conditions, their relation to a MC1 potential vegetation class is often many to one (table 1).

Given this constraint, one crosswalk approach is to select a single representative STSM stratum for each MC1 potential vegetation class for a landscape. Throughout this document, we will often provide examples and illustrate processes using the PVT concept for STSM stratum. With this approach, numerous aggregated PVTs will crosswalk to a particular MC1 vegetation class (Hemstrom et al. in press). Historical and future simulations with MC1, compared to locally derived maps, can guide the selection of the most representative PVTs for each landscape. It is important to consider whether or not the representative PVT fits the MC1

Table 1—Example showing the relationship between selected MC1 potential vegetation classes and locally representative potential vegetation types from a study area in eastern Oregon

MC1 Potential vegetation class	Description	STSM potential vegetation type
Subalpine forest	Subalpine forests in cold, upper elevation environments.	• Mountain hemlock (*Tsuga mertensiana* (Bong.) Carrière) – cold, dry • Shasta red fir (Abies × *shastensis* (Lemmon) Lemmon [*magnifica* × *procera*]) – dry • Subalpine woodland
Cool needleleaf forest	Mixed conifer forests in relatively moist mid- to upper-elevation forested environments.	• Mixed conifer – moist • Lodgepole pine (*Pinus contorta* Douglas ex Louden) – wet • Mixed conifer – cold dry • Cold dry forest • Cool moist forest
Temperate needleleaf forest	Mixed conifer forests in relatively dry mid- to lower elevation forested environments.	• Ponderosa pine (*Pinus ponderosa* C. Lawson var. *ponderosa*)/lodgepole pine – dry • Mixed conifer – dry • Ponderosa pine – xeric • Mixed conifer – dry (pumice soils) • Grand fir (*Abies grandis* (Douglas ex D. Don) Lindl.) – dry • Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) – dry • Lodgepole pine – dry

plant functional type concept. It may also be possible to fine tune MC1 so that local vegetation is better reflected in the broad vegetation classes (Hemstrom et al. in press). When developing representative PVTs to reflect the dynamics of vegetation in the future, additional PVTs that might become more common in the future need to be added to the mega-STSM. Adjacent regions that may represent potential future conditions in the area of interest can be assessed for relevant candidates. This approach assumes that extant PVTs already approximately represent the vegetation dynamics that MC1 simulates. The selected PVTs are, therefore, surrogates for future potential vegetation types that are assumed to have generally similar successional and disturbance dynamics. The resulting climate-sensitive mega-STSM would then consist of a combination of representative PVTs based on output from MC1 from the historical and future simulation periods. Transitions in the mega-STSM could then allow portions of the landscape to move among the previously independent PVTs according to output from MC1 run with the selected climate change scenarios.

Once the strata for a mega-STSM have been selected, and incorporated into a single model, there are a number of ways in which output from MC1 can inform changes in strata. For example, MC1 projects changes in potential vegetation classes for a particular climate change scenario (an emission scenario combined with a GCM). These changes, in turn, can be converted into probabilities, which can then be used to inform the transition probabilities in the mega-model (Hemstrom et al. in press). However, MC1 vegetation types can change quickly and unrealistically from year to year, so implementing simple annual changes among strata does not necessarily lead to reasonable model output, especially at a fine spatial or temporal scales grain. A feature of STSMs is that they can be configured to change transition probabilities over time; using transition multipliers, average transition rates can be shifted up or down in any year by proportions that range from zero (no transition occurs that year) to greater than one (the transition is larger than the long-term simulation period average that year). Modelers can compute the average annual transition rate for each potential vegetation climate change transition over the entire MC1 simulation period, then develop transition multipliers to shift the average annual rate up or down according to MC1 output for that climate change transition in that year. Using this technique, it is possible to reproduce the long-term average and the year-to-year variation simulated by MC1 for transitions between PVTs in the mega-STSM. Provencher and Anderson (2011) use a different method for incorporating climate change into their STSMs, but make similar use of transition multipliers. The conditions under which the STSM allows transitions due to climate change should be carefully considered and ecological constraints may be necessary to produce plausible dynamics. One approach is to only allow transitions between PVTs within the STSM following a stand-replacing disturbance (Provencher and Anderson 2011, Hemstrom et al. in press, Yospin 2012); alternatively, transitions from one potential vegetation type to another may occur under a broader set of circumstances.

A second approach to adjust transition probabilities for successional changes among strata and states over time in a mega-STSM is to use additional MC1 output beyond just its projected plant functional types. For example, Yospin (2012) developed a regression equation between MC1 output variables (e.g., soil carbon) that correlated reasonably well (r^2 = 0.55, $p < 0.001$) with site index, a measurement of the height to which a Douglas-fir will grow in 50 years. Forest stands representing current and potential plant communities were run through the Forest Vegetation Simulator (Crookston and Dixon 2005) at a wide range of site index values. The rates at which trees within these stands transitioned from one STSM state to another under different site indexes were then converted to annual transition probabilities. Using the regression equation, MC1 output was used to project future site index in each location over time, which in turn was used to select the appropriate transition probabilities for each location at each time step. Because site index and MC1 data were spatially explicit, this approach allows for spatially explicit simulations of climate change effects on site productivity.

These two types of adjustments to STSM transition probabilities account for changes in plant growth potential due to climate change, but do not capture the role of other climate-related effects. The impact of climate change on other stand-replacing disturbances also needs to be accounted for, and this is the focus of our third approach. Presently, MC1 does not provide projections regarding disturbance types other than fire, although researchers are currently working to incorporate insect and disease effects. Hemstrom et al. (in press) used projections for wildfire occurrence directly from MC1 and incorporated these into a mega-STSM. First, annual trends in wildfire probabilities from MC1 were calculated using the annual fraction of cells burned each year. For simplicity, and to reduce uncertainty, output was combined for several STSM strata (e.g. forest types, arid land types). MC1 can run without or with fire suppression using a set of algorithms that only allow intense stand-replacing fires to spread (Rogers et al. 2010). If MC1 is run without fire suppression, the projections for area burned are considerably higher than would be expected with fire suppression, but future projections of fire area burned can be scaled down using empirical datasets (e.g., the Monitoring Trends in Burn Severity data-set, Eidenshink et al. 2007, http://www.mtbs.gov). Alternately, MC1 can run with fire turned off during the historical period, the future period, or both periods. In this case, a separate statistical or mechanistic fire model would be required to provide projections of fire disturbance to the mega-STSM. By using a fire model outside of MC1, carbon and biogeochemical pools simulated by MC1 are decoupled from the fire effects, missing fire mortality and biomass consumption the model normally calculates. Furthermore, an external fire model would disregard the build-up of fuel and fuel moisture variability that serve as index to trigger fires in MC1.

There are also many other parameters within a STSM or mega-model that could change dynamically in response to changing climatic conditions. Mortality probabilities may need adjustment for drought-stressed trees under some climate scenarios (for examples, Provencher et al. 2009, Provencher and Anderson 2011). Yospin (2012) used a simple spatially-explicit rule base to attenuate growth potential across a landscape. The rule base restrictions prevent forests from growing larger trees or denser forest stands when MC1 indicated that climate did not support such growth, without summarily imposing mortality for the stand. This ecological restriction on both growth and mortality is a conservative approach to making the STM climate-sensitive. Simulations using a STSM parameterized with MC1 with the fire module turned completely off are one way to test the effect of climate independently from fire disturbance. For example, the direct effects of increased CO_2 and increased plant water use efficiency may accelerate some successional pathways, or allow larger amounts of carbon to be stored on the landscape, although this effect may be only marginal for some ecosystems. Users may also need to define additional states to capture such phenomena, or allow another model to specify those transitions.

One advantage of performing spatially-explicit simulations of vegetation dynamics with a STSM (e.g., Yospin 2012) is that spatially explicit land management actions can then be simulated in conjunction with climate-sensitive ecological succession. For example, the STSM developed by Yospin (2012) is being incorporated as a module within a larger modeling system named Envision. Envision is an agent-based model of landscape change that allows individual agents, representing different types of landowners, to make probabilistic land use and land management decisions based on the availability of resources, feedbacks from past actions, and in response to user-defined behaviors (Envision is a new model based on Evolan, Bolte et al. 2006, Guzy et al. 2008). Envision is one example from the broad array of agent-based social decision simulation models, many of which rely on simple STSMs of vegetation. Incorporating climate change into STSMs of vegetation may be an effective way to bring climate change effects into simulation modeling of landscape management.

Discussion and Conclusions

Developing vegetation STSMs that incorporate the possible effects of future climate change will broaden and enhance their utility, allowing managers and other users to explore the roles of various processes and agents of change on landscape-level vegetation dynamics. The empirical basis of STSMs makes possible a variety of approaches for incorporating the effects of climate change. We describe common challenges and four approaches using output from the DGVM MC1 to create climate-sensitive STSMs (Hemstrom et al. in press, Yospin 2012). These approaches hold promise because the DGVM can mechanistically project potential vegetation changes and fire with changing climate, while the mega-STSMs can apply these changes to locally relevant potential vegetation, impose realistic management actions, and mitigate the rapid rates of change allowed under DGVMs like MC1. We are currently producing example extrapolations of possible vegetation change from several climate change scenarios in different case study landscapes using these approaches. We expect these methods to be of considerable interest to others who use STSMs as well.

However, it is essential to recognize numerous caveats about all STSM-based approaches. Regardless of how STSMs are made climate-sensitive, they neither simulate physiological responses of vegetation nor project landscape states by simulating landscape processes mechanistically. Rather they are empirical models that must draw from a combination of other models and expert judgment to reflect the current understanding of system properties. In doing so, they can help researchers organize state-of-the-art knowledge and information, and serve as tools for assessing the potential ramifications of alternative management strategies. Because STSMs are probabilistic, a series of repeated simulations can be used to bracket a potential range of future conditions under changing climate. The results from these models can be informative for land managers working at a variety of spatial grains and scales. We see these approaches as promising avenues for improving landscape planning and assessments under the projected trends and uncertainties of climate change.

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