

Simulating vegetation response to climate change in the Blue Mountains with MC2 dynamic global vegetation model

John B. Kim^{a,*}, Becky K. Kerns^a, Raymond J. Drapek^a, G. Stephen Pitts^b, Jessica E. Halofsky^c

^a U.S. Forest Service, Pacific Northwest Research Station, Corvallis, OR, USA

^b Oregon State University, Corvallis, OR, USA

^c School of Environmental and Forest Sciences, University of Washington, Seattle, WA, USA

ARTICLE INFO

Keywords:

Climate change
Regional change
Simulation
Calibration
Forests
Fire
Dynamic global vegetation model

ABSTRACT

Warming temperatures are projected to greatly alter many forests in the Pacific Northwest. MC2 is a dynamic global vegetation model, a climate-aware, process-based, and gridded vegetation model. We calibrated and ran MC2 simulations for the Blue Mountains Ecoregion, Oregon, USA, at 30 arc-second spatial resolution. We calibrated MC2 using the best available spatial datasets from land managers. We ran future simulations using climate projections from four global circulation models (GCM) under representative concentration pathway 8.5. Under this scenario, forest productivity is projected to increase as the growing season lengthens, and fire occurrence is projected to increase steeply throughout the century, with burned area peaking early- to mid-century. Subalpine forests are projected to disappear, and the coniferous forests to contract by 32.8%. Large portions of the dry and mesic forests are projected to convert to woodlands, unless precipitation were to increase. Low levels of change are projected for the Umatilla National Forest consistently across the four GCM's. For the Walla-Walla and the Malheur National Forest, forest conversions are projected to vary more across the four GCM-based simulations, reflecting high levels of uncertainty arising from climate. For simulations based on three of the four GCMs, sharply increased fire activity results in decreases in forest carbon stocks by the mid-century, and the fire activity catalyzes widespread biome shift across the study area. We document the full cycle of a structured approach to calibrating and running MC2 for transparency and to serve as a template for applications of MC2.

Practical Implications

MC2 is a dynamic global vegetation model (DGVM), a simulation model designed to explore and estimate the long-term effects of climate change on vegetation. MC2 represents the landscape as a grid, and simulates processes that govern vegetation biogeochemistry, biogeography, and interactions with wildfire. Although MC2 has been applied to various regions, it has not been specifically calibrated for the Blue Mountains Ecoregion of eastern Oregon, USA, at a fine resolution. We calibrated and ran MC2 DGVM simulations for the Blue Mountains Ecoregion at the finest possible resolution of 30 arc-seconds, and obtained projections of vegetation response to climate change for the historical period 1895–2008, and from 2009 to 2100 under representative concentration pathway (RCP) 8.5 climate change scenario.

Although many publications describe facets of applying MC2 (and its precursor, MC1) to a region and provide some parameter values, no paper articulates a structured approach to calibration to serve as a template for future studies. In this paper, we describe the full modeling lifecycle of applying MC2 DGVM to the Blue Mountains Ecoregion within the context of science-management partnership collaboration, to serve as a template to emulate and improve upon, as well as to make the modeling process more transparent end-users of the simulation products.

Under the RCP8.5 climate change scenario, MC2 projects substantial changes for the forests of the Blue Mountains Ecoregion by the end of the century. The growing season is projected to lengthen, leading to forest productivity increases. Fire occurrence is projected to increase sharply throughout the century, with burned area peaking early- to mid-century, and forest carbon stocks dipping at those times. These early- to mid-century changes are projected to coincide with major

* Corresponding author at: U.S. Forest Service, Pacific Northwest Research Station, 3200 SW Jefferson Way, Corvallis, OR 97331, USA.
E-mail address: jbkim@fs.fed.us (J.B. Kim).

shifts vegetation types. Subalpine forests are projected to disappear by the end of the century. Moist forests are projected to remain relatively stable under this scenario, while large portions of the mesic and dry temperate forests may convert to woodlands and shrublands. If precipitation were to increase under climate change, moist forests may expand.

For a single climate change scenario, general circulation models (GCM) project somewhat different future climate conditions. We drove MC2 simulations with climate projections from four GCMs and the results are the most consistent for Umatilla National Forest, where the moist needleleaf forest dominates. There is less agreement in the Wallowa-Whitman and the Malheur, where there are high fractions of mesic and dry temperate needleleaf forests, which may convert to woodlands and shrublands under climate change. Many parts of the lower-elevation shrublands are projected to convert from temperate vegetation types to subtropical vegetation types, which may include some C4 vegetation if summer precipitation increases significantly.

Although the patterns of change simulated in this study agree in broad terms with other studies in the region, there are some important differences. This highlights the importance of obtaining a good calibration tailored to the region of interest, using quality benchmark data to validate the model calibration. In the simulations, fire exerts a strong control on the forests, and is therefore a source of uncertainty, as well as an opportunity to improve the model skill and calibration.

1. Introduction

Climate is already changing in the Pacific Northwest (Abatzoglou et al., 2014), and is projected to warm by 5.0 °C by the end of the century (Rupp et al., 2016) under representative concentration pathway 8.5 (RCP8.5), the “no mitigation” baseline climate change scenario (Riahi et al., 2011). Under this scenario, climate of the Pacific Northwest will change with a horizontal velocity exceeding 0.11 km yr⁻¹ (Loarie et al., 2009), and will permanently depart historical climatic conditions by the year 2050 (Kerns et al., 2016). Warming temperatures are projected to greatly reduce available climate niches for many forest species in the Pacific Northwest (McKenzie et al., 2003; Rehfeldt et al., 2006), drive massive dieback of conifers (McDowell et al., 2015), increase fire frequency and severity (Rogers et al., 2011; Westerling et al., 2006), and bring episodes of hazardous air quality (Thompson et al., 2011). Like most of the western US, climate can vary considerably with elevation in the Blue Mountains Ecoregion, a 7.2 Mha ecoregion in the Pacific Northwest (Omernik, 1987), and the effects of climate change may vary greatly across elevation gradients. In order to understand the range of potential future vegetation change in mountainous areas, information from vegetation models is needed at relatively fine spatial scales. The availability of model output at fine scales also facilitates applying model-based projections to potential management responses.

The rapid, dynamic and complex nature of impending climate change necessitates the use of modeling tools that can account for the complexities of changing climate and the potential for novel conditions. Although species distribution models are appealing due to their ability to hindcast observed biogeography, they may have poor predictive performance under new climates when past correlative relationships do not apply (Bell and Schlaepfer, 2016; Kerns et al., 2017a). MC2 is a dynamic global vegetation model (DGVM), a climate-aware, process-based, spatially explicit vegetation model that represents the landscape as a grid. MC2 is driven with long-term future climate projections and has the ability to project future vegetation and wildfire under no-analog climate conditions (Bachelet et al., 2001; Conklin et al., 2016).

There have been many MC1 and MC2 simulations located in the Pacific Northwest (Table S1). However, some simulations cover a nearby area but do not cover the Blue Mountains Ecoregion (BME) (Halofsky et al., 2013, 2014b, 2017; Yospin et al., 2015), while others cover only a portion of BME (Rogers et al., 2011; Creutzburg et al., 2015). There are continental- and global-scale simulations that include the Blue Mountains Ecoregion—e.g., a simulation of North America at 5 arc-minute (approximately 8 km) resolution (Drapek et al., 2015a,b), a 30 arc-second (~800 m) resolution simulation of the conterminous U.S. (Bachelet et al., 2015a), a global simulation at 50 km resolution (Gonzalez et al., 2010), and another global simulation at the 0.5° resolution (Kim et al., 2017)—but the relatively coarse resolutions used in those studies preclude capturing the finer scale elevation-based vegetation types in the current study area. Coarser resolution models represent a barrier to extracting applicable information from simulations at the scale of potential management responses. Furthermore, in those simulations MC1 or MC2 was calibrated at the continental or global scale, which lead to the use of plant functional types that are broadly defined and not parameterized specifically to the historical vegetation of the Blue Mountains Ecoregion. Yet another limitation of the aforementioned simulations is that with the exception of Creutzburg et al. (2015) and Kim et al. (2017), the future projections were based on Special Report on Emissions Scenarios (SRES) emissions scenarios (e.g., A2, A1B, B1), not the more recent representative concentration pathways (RCP) climate change scenarios (Van Vuuren et al., 2011) used in the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). Sheehan et al. (2015) describe a 1/24° (~4 km) resolution simulation of the Pacific Northwest using RCPs, which has some applicability to BME. A potential limitation of the simulation by Sheehan et al. (2015) is that it applied the continental-scale calibration from Bachelet et al. (2015a) to just the Pacific Northwest. It also does not take advantage of regionally available input and calibration datasets.

To overcome the limitations of existing MC1 and MC2 simulations in terms of their spatial coverage, resolution and calibration, we calibrated and ran MC2 DGVM simulations specifically for the Blue Mountains Ecoregion at the finest possible resolution of 30 arc-seconds, using RCP8.5-based climate change projections to drive simulations of future vegetation dynamics. The spatial resolution in the present study (30 arc-seconds) is determined by the availability of historical gridded climate data (PRISM, Daly et al., 2008). The historical gridded climate data is required to calibrate the model for historical vegetation conditions. In addition, because general circulation models (GCM) simulate climate at a coarse scale (1–2.5°), the historical gridded climate data is used to downscale GCM output, and thereby dictates the resolution of the final downscaled climate projection data. At 30 arc-second resolution, MC2 is better able to represent elevation-based vegetation ecotones and forest boundaries in BME.

The strategic application of a DGVM may have a useful role in regional climate change adaptation planning. The availability of appropriate technical tools and their acceptability by local end-users remain barriers to climate change adaptation (Moser and Ekstrom, 2010). Many science-management partnership efforts in the Pacific Northwest and beyond have demonstrated that a collaborative approach to synthesize climate change tools and options can be effective (Halofsky and Peterson, 2016). Effectively applying a DGVM to regional planning can be difficult because each DGVM with its unique formulation exhibits regional biases (Sitch et al., 2008), and finding good quality input data and calibrating the model to fine-scale spatial processes is a lengthy and challenging process (Bachelet et al., 2015b). These challenges suggest a need for a clearly articulated approach for calibrating and evaluating a dynamic global vegetation model at the regional scale. Although a few MC1 or MC2 simulation papers provide brief outlines of the calibration process (e.g., Sheehan et al., 2015; Kim et al., 2017), most regional simulation papers provide little to no descriptions of the calibration and validation process (e.g., Bachelet et al., 2015a, 2016; King et al., 2013; Yospin et al., 2015; Halofsky et al., 2013), probably due to limitations

on paper length and focus. Some papers provide detailed parameter values (e.g., [Creutzburg et al., 2015](#); [Drapek et al., 2015b](#); [Rogers et al., 2011](#)), but do not provide a description of the overall approach, which makes simulations difficult to reproduce or emulate.

In this paper, we describe the full modeling lifecycle of applying MC2 DGVM to the Blue Mountains Ecoregion within the context of science-management partnership collaboration. We outline all the essential steps in the modeling workflow. We demonstrate the methodologies for assembling input data, calibrating and evaluating the model. Our aim is to document the process of applying the MC2 DGVM at a regional scale, so that the methodology is more transparent to the end-user community in the Blue Mountains Ecoregion and to the general modeling community. We also analyze key simulation output data to describe the broad-scale patterns and drivers of vegetation response simulated by MC2. This analysis is intended to complement the exploration of climate change effects on vegetation using multiple lines of evidence ([Kerns et al., 2017b](#)), by providing details about the MC2 simulation results not covered in [Kerns et al. \(2017a\)](#).

2. Methods

2.1. Study area

The Blue Mountains Ecoregion (BME) is a US EPA Level 3 ecoregion ([Omernik, 1987](#)) located in Northeastern Oregon, a 7.2 Mha complex of mountains and basins ranging in elevation from 186 m to 2658 m, with an average elevation of 1292 m. ([Fig. 1](#)). Most of the mountains in the region are volcanic in origin, although the Wallowa and Elkhorn Mountains are composed of granitic intrusives, deep sea sediments, and metamorphosed rocks ([Thorson et al., 2003](#)). Soil depth ranges from 15 cm to 254 cm, with an average of 96 cm according to soil dataset produced by the Integrated Landscape Assessment Project (ILAP) ([Halofsky et al., 2014a](#)). The climate of the region is Mediterranean, with mean annual temperature of 7.5°C and average annual precipitation of 518 mm, with most of the precipitation falling in the winter, as both rain and snow. The lower elevations of the ecoregion comprise grasslands, shrublands, and juniper woodlands. Dry conifer forests occupy the lower montane zone, with ponderosa pine (*Pinus ponderosa*), Douglas-fir (*Pseudotsuga menziesii*), and grand fir (*Abies grandis*). In the upper montane forests include Douglas-fir, grand fir,

and subalpine fir (*Abies lasiocarpa*). At high elevations, Engelmann spruce (*Picea engelmannii*), subalpine fir, and whitebark pine (*Pinus albicaulis*) dominate. Grazing, fire suppression and selective logging of economically valuable trees is common across the ecoregion. [Halofsky and Peterson \(2016\)](#) describes the biogeography and climate of this region in greater detail and [Kerns et al. \(2017b\)](#) describe the vegetation of the region in greater detail.

MC2 simulation was performed as a component of the Blue Mountains Adaptation Partnership (BMAP), a science-management partnership among the U.S. Forest Service Pacific Northwest Research Station, Pacific Northwest Region, Oregon State University, and resource managers in the Wallowa-Whitman, Umatilla, and Malheur National Forests. When formed, BMAP was one of the largest climate change vulnerability assessments in area on federal lands in North America ([Halofsky et al., 2015](#)). The vulnerability assessment was subsequently used to develop resource management tools and techniques that will facilitate adaptation to a changing climate. Our primary contact for obtaining data and guidance on model application was the Blue Mountains Restoration Strategy Interdisciplinary Team, a group of nine Forest Service scientists and resource managers already working on rapidly restoring resiliency to the Blue Mountains after more than a century of fire suppression. Through the restoration team, we obtained the best available spatial datasets to use as model input or evaluation benchmarks, including soil surveys, climate and fire data, and vegetation distribution maps.

2.2. Overview of MC2 DGVM structure

MC2 is the computationally efficient but functionally equivalent version of MC1 DGVM, rewritten in C++. Because MC2 design and structure are described in detail elsewhere ([Bachelet et al., 2001](#); [Conklin et al., 2016](#)), we summarize only the relevant characteristics of MC2 here and specific methods employed for the current study. MC2 comprises three submodels ([Fig. 2](#)): the CENTURY Soil Organic Matter Model ([Parton et al., 1993](#)), which simulates ecosystem carbon and water balance; the MC-Fire fire simulation model ([Conklin et al., 2016](#)); and the MAPSS vegetation biogeography model ([Neilson, 1995](#)). Vegetation is represented as one of many plant functional types (PFT) ([Table 1](#)). The CENTURY and MC-Fire submodels run on a monthly time step. The CENTURY submodel simulates competition for light, water

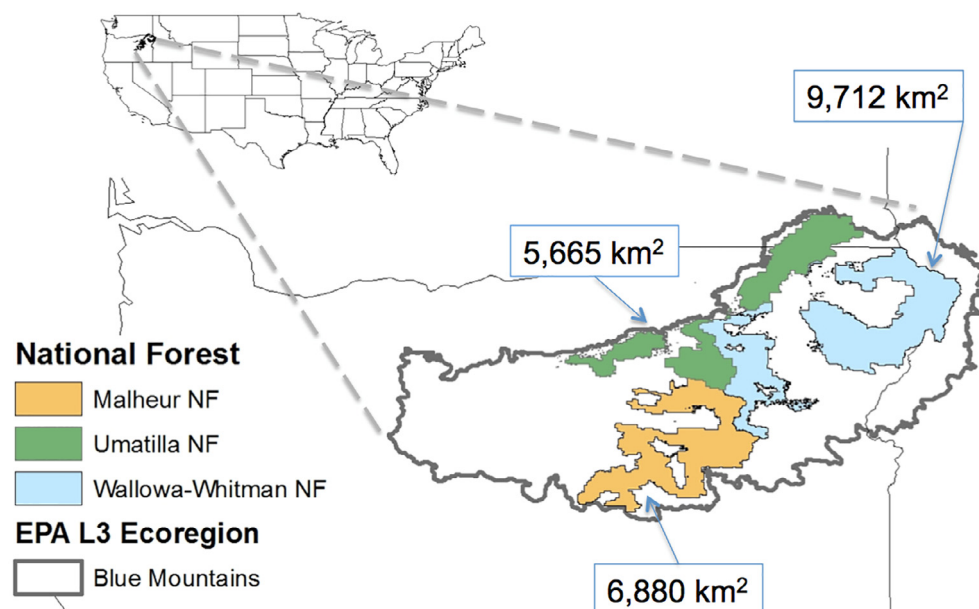


Fig. 1. Blue Mountains Ecoregion (BME) is a US EPA Level 3 ecoregion ([Omernik, 1987](#)) located in northeastern Oregon, United States, with some portions in Washington and Idaho. BME encompasses three national forests: Malheur NF, Umatilla NF and Wallowa-Whitman NF.

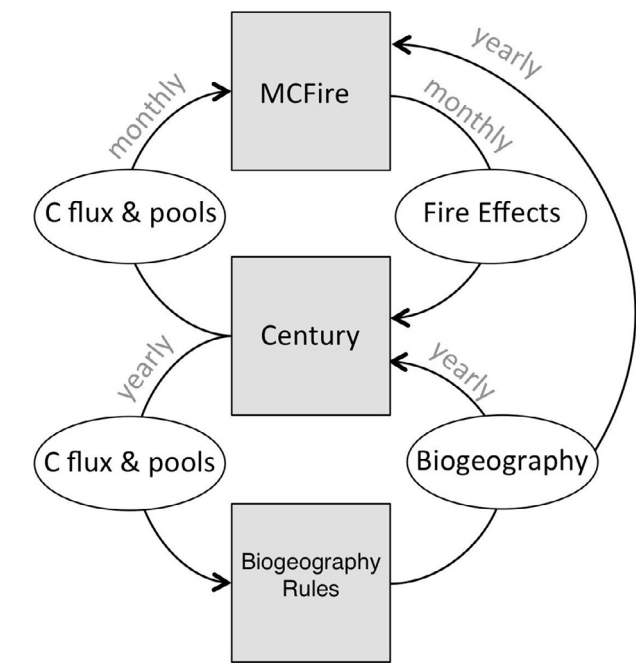


Fig. 2. MC2 is comprised of three distinct submodels. The Century submodel simulates ecosystem carbon and water balance, and passes ecosystem state to the MCFire submodel every month. Fire effects calculated by MCFire submodel is passed to the Century submodel each month. A biogeography submodel consisting of biogeography rules is invoked at the end of each year, and its classification of each grid cell into a vegetation is passed back to the other two submodels.

Table 1
Crosswalk between Potential Vegetation Types (PVT) by Integrated Landscape Assessment Project (ILAP) (Halofsky et al. 2014a,b) and MC2 plant functional types (PFT).

ILAP PVT	MC2 PFT
Subalpine woodland Mountain hemlock – cold/dry Subalpine fir – cold/dry Subalpine meadows – green fescue	Subalpine forest
Grand fir – cool/moist	Moist temperate needleleaf forest
Grand fir – warm/dry Mixed conifer – cold/dry Douglas-fir – dry	Mesic temperate needleleaf forest
Ponderosa pine – dry, with juniper Ponderosa pine – xeric	Dry temperate needleleaf forest
Western juniper woodland Mountain big sagebrush – with juniper Mountain mahogany Low sage – mesic, with juniper	Temperate needleleaf woodland
Montane and canyon shrubland Bitterbrush – with juniper Wyoming big sagebrush – with juniper Wyoming big sagebrush – no juniper Low sage – mesic, no juniper Rigid sage Threetip sage	Temperate shrubland
Salt desert shrub – upland Salt desert shrub – lowland	Subtropical shrubland
Bluebunch-wheatgrass – Sandberg bluegrass Idaho fescue – Prairie junegrass	Temperate grassland

and nutrients between a single representative tree PFT and a grass PFT. Primary productivity is simulated by calculating net primary productivity (NPP) of tree and grass as a function of air temperature, soil

water availability, leaf area index, and CO₂ concentration. The tree PFT and grass PFT compete for soil water, and the tree PFT may shade grass, limiting its NPP. The ecosystem state is passed to MC-Fire each month (Fig. 2).

The MC-Fire submodel is designed to project long-term fire effects on vegetation, not the dynamics of individual fires. It uses a random weather generator to simulate daily weather and fuel conditions (Conklin et al., 2016). Fire occurrence is simulated when fuel conditions exceed two thresholds (build-up index and fine fuel moisture code). The fire module calculates fraction of the grid cell burned as a reciprocal of the prescribed fire return interval. Fire severity for the grid cell, including the occurrence of a canopy fire, is calculated for a single representative tree. Fire does not spread across cells, and is limited to one occurrence per grid cell per year. Fire effects are passed back to the CENTURY submodel.

At the end of each simulated year, a biogeography submodel classifies the ecosystem state of the grid cell into a plant functional type (PFT). PFTs are used, in turn, to look up fire regime parameters, including fire occurrence thresholds and return intervals.

2.3. Preparing simulation input data

MC2 requires various gridded input files: elevation data, climate data (temperature, precipitation and vapor pressure), and soils data. All datasets must be resampled and registered to the same coordinate system.

Climate data covering two periods are needed: historical and future. For historical, we used PRISM climate data (Daly et al., 2008), available in 30 arc-second resolution (~800 m at this latitude). For future climate projections, we considered downscaled climate data products based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) GCM outputs, available through the Earth System Grid Federation (Cinquini et al., 2014). When this project commenced, the finest scale downscaled CMIP5 climate projections covering the study area was 1/24° (~4 km) spatial resolution. Based on guidance from the Blue Mountains Restoration Strategy Interdisciplinary Team, our primary contact for resource managers, that 4 km resolution is too coarse for adaptation planning in the Blue Mountains Ecoregion, we opted to downscale GCM outputs to 30 arc-second spatial resolution, using the Delta Method (Fowler et al., 2007) with PRISM climate data (Daly et al., 2008) as the reference historical climate dataset. We chose to use RCP8.5 climate change scenario as a reference case, representing a future without an effective global mitigation policy.

Over 30 GCM outputs have been published online by CMIP5. We selected four GCM outputs so that the selected set spans a plausible range of possible future climate conditions, as characterized by mean annual temperature and precipitation, while avoiding GCM's with poor skill for simulating historical climate of the Pacific Northwest (Rupp et al., 2013). We selected CSIRO-Mk3.6.0 for its proximity to RCP8.5 ensemble mean, HadGEM2-ES to represent the greatest warming, MRI-CGCM3 to represent the least warming, and NORESM1-M to represent a wetter climate (Fig. 3). We downscaled four climate variables required by MC2: monthly averages of daily maximum and minimum temperatures, precipitation and vapor pressure. For vapor pressure, we first calculated it from surface specific humidity and surface air pressure, then downscaled to 30 arc-seconds.

For soils data, MC2 requires soil texture for 3 layers (0–50 cm, 50–150 cm, and > 150 cm), where texture is quantified as percent rock, sand, silt and clay. Total soil depth and bulk density are also required. Using the best available soil dataset is critical, because soil data can exert a strong effect on ecosystem carbon simulated by MC2 (Peterman et al., 2014). We consulted with resource managers and identified a suitable soil dataset, developed in the Integrated Landscape Assessment Project (ILAP) (Halofsky et al., 2014a). ILAP summarized rock, sand, clay and silt percentages, along with soil depth and bulk density, from Soil Survey Geographic Database (SSURGO) and State Soil Geographic

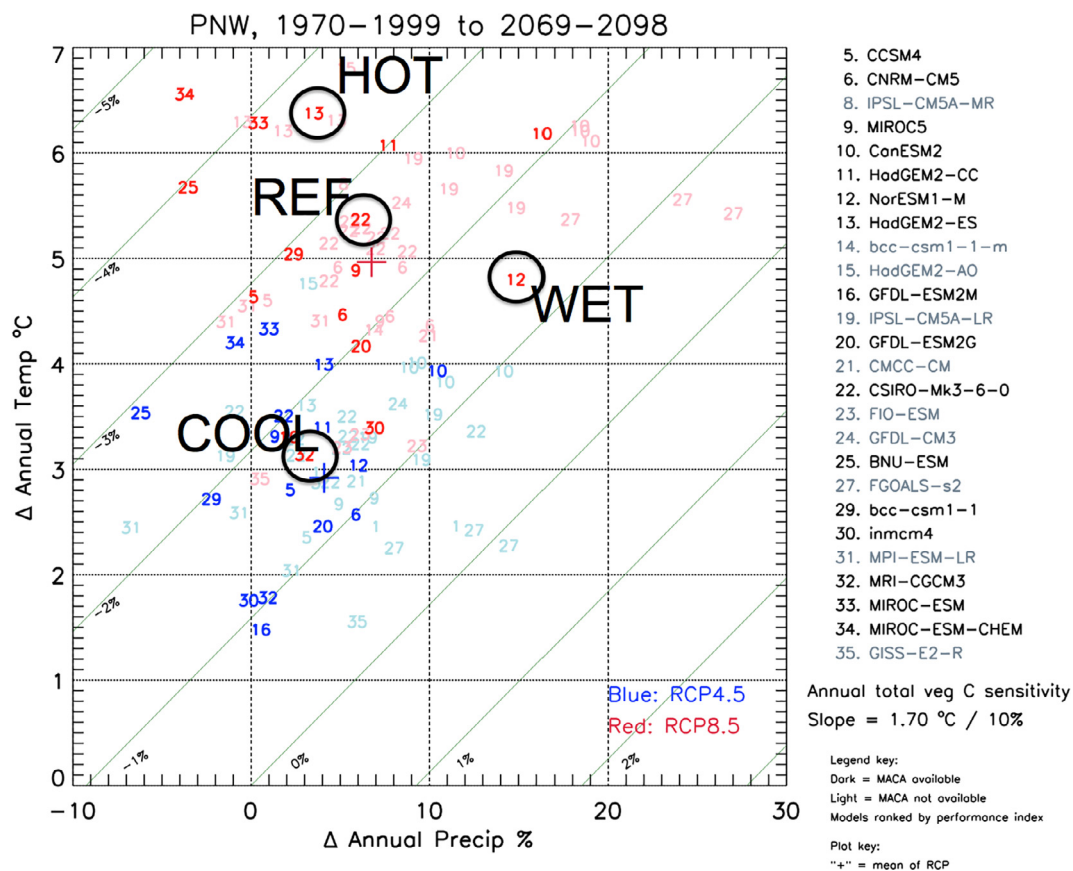


Fig. 3. Climate projections were selected from published CMIP5 RCP8.5 datasets by selecting general circulation models (GCM) that span the range of values in mean annual temperature and precipitation, while avoiding GCMs with low model skill per Rupp et al. (2013). CSIRO-Mk3.6.0 (labeled “REF” for reference) was selected for its proximity to the ensemble mean. HadGEM2-ES (“HOT”), MRI-CGCM3 (“COOL”) and NorESM1-M (“WET”) were selected for their positions relative to the ensemble mean.

Database (STATSGO) tabular data (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2016), joined those summary values to source feature polygon data from the Natural Resources Conservation Service, and then converted the data to 30 arc-second raster using the cell center to assign the values.

2.4. Modeling protocol

MC2 must be run in multiple phases, with the end state of one phase saved and used as the initial state of the next phase. In the first phase, MC2 is run with 30-year monthly climatology representing the period 1895–1924, to equilibrate its internal states to that period’s climate. Secondly, MC2 is run with a detrended version of the 1895–2008 transient climate data for over a hundred iterations, to allow its slow-changing soil carbon pools to reach an equilibrium state. The third phase is the historical simulation, run with 1895–2008 climate data. Finally, each future scenario is simulated starting with the model state saved from year 2008. Future simulations are run from 2009 to 2100. We ran the historical simulation with fire suppression turned on, in order to calibrate the model to observation data; and we ran the future simulations with fire suppression turned off, to provide resource managers a base case where vegetation and fire interact without direct intervention.

2.5. Model calibration & evaluation

At the selected spatial resolution (30 arc-seconds, ~800 m) the Blue Mountains Ecoregion is represented by 111,067 grid cells, and MC2 requires 7 h to simulate 100 years on a typical desktop computer. We

selected every 6th grid cell along latitude and longitude (2.8% of all grid cells) to create a small sample grid for use in calibration. A historical simulation of the sample grid completed in less than 20 min, enabling rapid, repeated calibration runs.

National forest ecologists and land managers were generally familiar with ILAP potential vegetation types (PVT) but not familiar with the plant functional types (PFT) that MC2 simulates. To make MC2 results more useful to national forest managers, we developed a cross-walk between ILAP PVT and MC2 PFT (Table 1). Generally, multiple ILAP PVTs were lumped and associated with a single MC2 PFT. For example, many ILAP upland forest types were initially cross-walked into a single MC2 PFT, the temperate needleleaf forest. However, because national forest managers were interested in potential future conditions for different upland forest types, we split the temperate needleleaf forest PFT into three distinct PFTs: moist, mesic and dry forest. We modified the MC2 biogeography algorithm so that average annual precipitation would be used to distinguish among the three PFTs.

We calibrated MC2 systematically by following steps that mirror MC2’s structural design (Fig. 4). We first calibrated simulated net primary productivity (NPP), biome biogeography, and PFT biogeography without simulating fire occurrence, comparing MC2 outputs for the recent historical period with related benchmark datasets obtained from and/or in consultation with project partners. Once NPP and biogeography were initially calibrated, we enabled MC2 to simulate fire occurrence and calibrated the fire parameters. After completing the fire calibration, we returned to fine-tuning NPP and biogeography further, since simulated fire effects may have significant effects on NPP and biogeography.

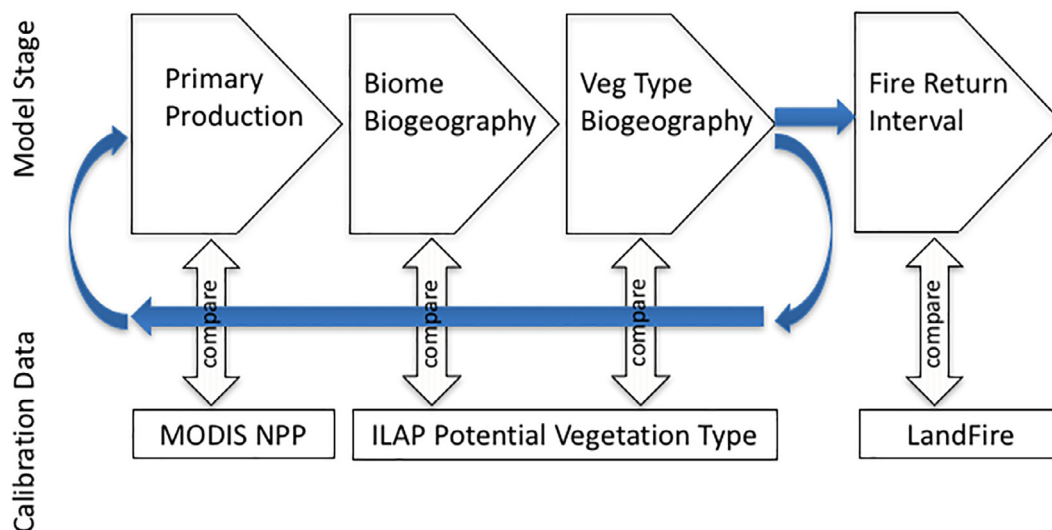


Fig. 4. We calibrated MC2 systematically by following steps that mirror MC2's structural design. We used benchmark datasets obtained from stakeholders.

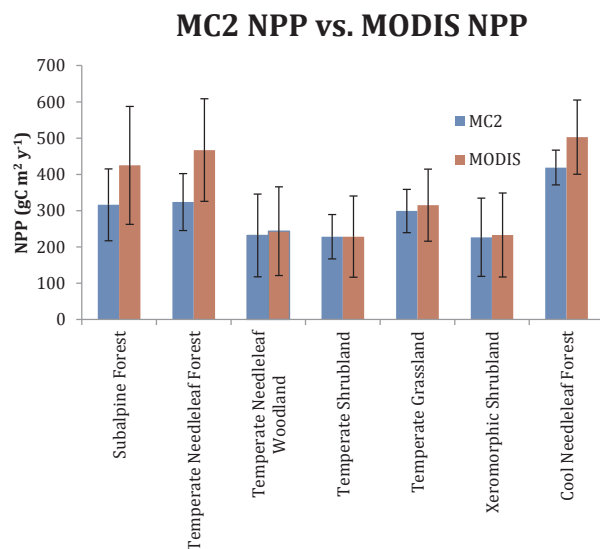


Fig. 5. Net primary production (NPP) simulated by MC2 for 2000–2009 vs. NPP per MODIS (Zhao et al., 2005), averaged per MC2 plant functional type for the study area.

We compared and calibrated MC2 NPP to MODIS Terrestrial Gross and Net Primary Production Global Data Set, version MOD17 (Zhao et al., 2005). Although MODIS NPP is not a pure observational dataset, and includes many assumptions, it is the only gridded NPP dataset for the study area. MC2 calculates NPP as a function of available soil moisture and air temperature. For this calculation, MC2 locates each grid cell along a gradient that spans four leaf phenology-morphology types: deciduous-needleleaf (DN), evergreen-needleleaf (EN), deciduous-broadleaf (DB) and evergreen-broadleaf (EB) (Daly et al., 2000). MC2 calculates NPP for each leaf phenology-morphology type using its own set of parameters. We adjusted the parameter controlling the maximum NPP values for the four leaf phenology-morphology types, until reasonable correspondence with MODIS NPP was obtained for each PFT in the study area (Fig. 5). On average, MC2 slightly underestimated NPP given by MODIS for each PFT, with a similar range of values.

Biome and PFT biogeography are determined by a rule-based algorithm within MC2 (Neilson 1995; Bachelet et al., 2001). The algorithm first classifies a given grid cell into one of five biomes—desert, grassland, shrubland, woodland and forest—by comparing simulated

forest carbon stocks and grass NPP to threshold values. We adjusted those threshold values so that the biome biogeography simulated by MC2 matched the biogeography of ILAP PVTs. MC2 further classifies each grid cell into one of 30 internally defined PFTs (many of which, such as the tropical PFTs, are not invoked by the algorithm for this study area). This classification is done by comparing simulated vegetation carbon stocks and NPP, plus temperature, precipitation, leaf phenology and morphology information, against threshold values. We primarily adjusted the precipitation thresholds so that the biogeography of forest types reasonably matched that given by the ILAP PVT map (Fig. 6). MC2 simulates the overall biogeography of the biomes with reasonable accuracy, locating moist temperate needleleaf forests in the Umatilla National Forest, and a mix of subalpine forests and the temperate forests in the Wallowa-Whitman National Forest. MC2 has some difficulty simulating the dominance of mesic temperate forests in the Malheur National Forest, as well as the mix of woodlands, shrublands and grasslands in the southern and southwestern reaches of the study area. ILAP PVT data show large subregions of temperate grassland in the northern sector, surrounding the two national forests, while MC2 simulates those areas as mesic temperate forests. That difference may arise from the soil data overestimating the soil depths, leading to higher soil moisture content and greater plant productivity. Conversely, ILAP PVT data may represent some bias toward grass dominance in those areas because much of the area is currently used as rangeland, and ILAP PVT data are derived in part from observation data (Halofsky et al., 2014a).

For calibrating simulated fires in MC2, we adjust parameters that control fire occurrence and those that control the fraction of the grid cell burned. MC2 simulates fire occurrence in a given cell (not the ignition process, natural nor anthropogenic) by calculating fuel conditions from the climate data, and comparing them against threshold values. Specifically, it calculates the fine fuel moisture code (FFMC), a fuel moisture code representing the litter layer and other cured fine fuels; and build-up index (BUI), a fire behavior index representing total fuel available for consumption (Van Wagoner, 1987). When MC2 simulates fire occurrence for a given grid cell, it calculates the fraction of the grid cell burned as a function of the number of years since the last fire occurrence for that grid cell, and the prescribed fire return interval for the PFT of the grid cell.

To calibrate MC2's fire dynamics, we used a recent calibration of MC2 for Central Oregon (Halofsky et al., 2013) as a starting point, and we further adjusted FFMC and BUI thresholds (Table 2) and the prescribed fire return intervals for each PFT (Tables 3, 4). We used LAN-DFIRE Rapid Assessment Vegetation Model (Beukema et al., 2003;

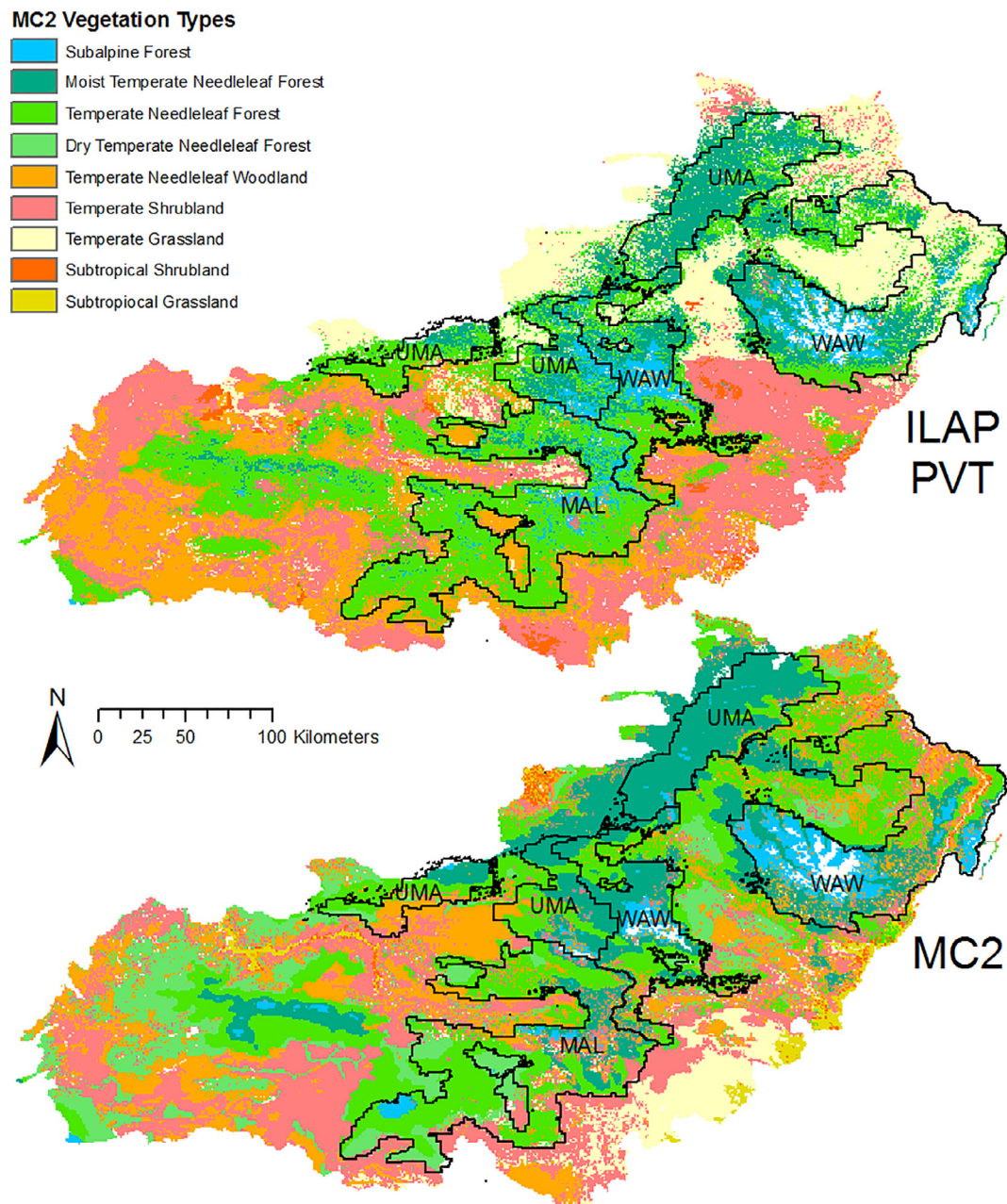


Fig. 6. Integrated Landscape Assessment Project (ILAP) (Halofsky et al., 2013) Potential vegetation type (PVT) translated into MC2 plant functional type (PFT) (top), compared with MC2 PFT output for 1970–1999 period (bottom). Boundaries of Umatilla (UMA), Wallowa-Whitman (WAW) and Malheur (MAL) National Forests are shown in black.

Hann et al., 2008; The Nature Conservancy, USDA Forest Service, and Department of the Interior, 2005) as benchmarks. We compared mean fire return intervals resulting from MC2 simulations against fire return intervals calculated from the LANDFIRE dataset. We compared area-weighted means of the fire return intervals for each PFT.

3. Results

Under RCP8.5 climate change scenario, MC2 projected broad-scale changes in the distribution of forest types within the Blue Mountains Ecoregion by the end of the century (Fig. 7). Simulations based on all four GCM's projected that the subalpine forests in the high elevation portions of Wallowa-Whitman National Forest will convert to moist temperate forests. With all simulations except for the one driven by the “wet” GCM (NORESM1-M), moist needleleaf forests remained relatively

stable between the historical period (1979–2008) and the end of the century (2071–2100), but temperate and dry temperate needleleaf forests converted to woodlands during that time (Figs. 7b, 8a). With the “wet” GCM (NORESM1-M), moist temperate needleleaf forest expanded greatly, from 17% of the ecoregion in the historical period (1979–2008) to 32% by the end of the century (2070–2099) (Fig. 8a), gaining area through conversions from dry and mesic needleleaf forests, as well as conversions from subalpine forests.

The ensemble of simulation outputs exhibited strong agreement in three broadly defined areas within the Blue Mountains Ecoregion (Fig. 7f). One, the existing distribution of moist temperate forests—which occur largely in Umatilla National Forest and to a lesser extent in Wallowa-Whitman National Forest—remain stable under these climate projections. The agreement is the strongest in the northernmost district of Umatilla National Forest, where none of the simulations

Table 2

Fire occurrence thresholds, compared with values calibrated for the Central Oregon simulation by Halofsky et al. (2013) and model default values for the conterminous U.S. Fine fuel moisture code (FFMC) and build-up index (BUI) represent fuel conditions (Van Wagoner, 1987).

MC2 PFT	Blue Mountains Ecoregion		Central Oregon		Default	
	FFMC	BUI	FFMC	BUI	FFMC	BUI
Subalpine Forest	90.85	150	89.14	245	89.14	122.85
Moist Temperate Needleleaf Forest	91.7	185	89.14	245	89.14	122.85
Temperate Needleleaf Forest	91.75	200	89.14	245	89.14	122.85
Dry Temperate Needleleaf Forest	91.4	215	n.a.	n.a.	n.a.	n.a.
Temperate Cool Mixed Woodland	89.14	122.85	89.14	245	89.14	122.85
Temperate Needleleaf Woodland	94.5	311	89.14	245	89.14	122.85
Temperate Shrubland	92.5	235	89.14	245	89.14	122.85
Temperate Grassland	91.5	122.85	89.14	245	89.14	122.85
Subtropical Shrubland	95	343	89.14	245	89.14	122.85

Table 3

Prescribed fire return intervals for the Blue Mountains Ecoregion, compared with values calibrated for the Central Oregon simulation by Halofsky et al. (2013), and model default values for the conterminous U.S.

MC2 PFT	Blue Mountains Ecoregion (yr)	Central Oregon (yr)	Default (yr)
Subalpine Forest	170	300	300
Moist Temperate Needleleaf Forest	200	50–150	50–150
Temperate Needleleaf Forest	197	50	50
Dry Temperate Needleleaf Forest	80–190	n.a.	n.a.
Temperate Cool Mixed Woodland	55	15	15
Temperate Needleleaf Woodland	542	15	15
Temperate Shrubland	161	30	30
Temperate Grassland	57	7	15–32
Subtropical Shrubland	1666	30	30

Table 4

Calibrated mean fire return intervals from MC2 and from LANDFIRE Rapid Assessment Vegetation Model (Beukema et al., 2003; Hann et al., 2008; The Nature Conservancy, USDA Forest Service, and Department of the Interior, 2005).

MC2 PFT	MC2 MFRI (yr)	Landfire MFRI (yr)
Subalpine Forest	224	170
Cool Moist Needleleaf Forest	195	200
Mesic Temperate Needleleaf Forest	142	197
Cool Dry Needleleaf Forest	150	130
Temperate Needleleaf Woodland	335	541
Temperate Shrubland	326	161
Temperate Grassland	15	57
Subtropical Shrubland	79	1666
Subtropical Grassland	5	n.a.

project the moist temperate needleleaf forest to shift into different types of forests. The agreement is weaker in the more southern districts of Umatilla National Forest, where one or two simulations do project shifts into other forest types. A second area of strong agreement occurs in the subalpine forests in the high elevation areas of the Wallowa-Whitman

National Forest. Simulations driven by all four GCM's project that these subalpine forests will disappear, converting to moist temperate needleleaf forests (Figs. 7f, 8c). The third area of strong agreement covers much of the southern half of the Blue Mountains Ecoregion, where all four simulations project conversion of the temperate shrublands and grasslands to subtropical shrublands and grasslands. The majority of this type shift occurs at the drier, lower elevation landscapes outside of national forests. MC2 distinguishes temperate plant functional types from subtropical ones primarily by applying a climate threshold on average annual temperature; the difference is not driven simulation of a complex physiological mechanism.

Each of the three national forests is exposed to climate change and its uncertainties in a different way (Fig. 8). Uncertainty from the choice of GCM used to drive the simulations is represented by the spread of the projected proportions of each plant functional type within a national forest (Fig. 8). For example, in the Umatilla National Forest, the projected proportions of temperate needleleaf woodland are nearly the same for all the GCM's, although generally higher than the historical proportion (Fig. 8b). In this case, the GCM's contribute little uncertainty to the projections. In contrast, there is far greater uncertainty with moist temperate needleleaf forests, which has historically dominated Umatilla National Forest. This is evident when comparing the results based on the "reference" GCM (CSIRO-Mk3.6.0), the "cool" GCM (MRI-CGCM3), and the "wet" GCM (NORESM1-M). In the projection based on the "reference" GCM (CSIRO-Mk3.6.0), plant functional type fractions remain relatively stable into the future, where a small fraction of the forests contract while woodlands and shrublands expand (Fig. 8b). In the projection based on the "cool" GCM (MRI-CGCM3), there is a greater loss of the moist temperate needleleaf forest, while in the projection based on the "wet" GCM (NORESM1-M) moist temperate needleleaf forest significantly expands at the expense of temperate needleleaf forest.

Relative to model projections for Umatilla National Forest, model projections for Wallowa-Whitman and Malheur National Forests exhibit greater uncertainty (Fig. 8c, d). The projected distributions of moist temperate needleleaf forests, woodlands and shrublands in these national forests have a wider range of outcomes depending on the GCM's. For example, the moist temperate needleleaf forests in the Malheur are projected contract somewhat based on the "cool" GCM (MRI-CGCM3) but nearly triple in extent based on the "wet" GCM (NORESM1-M). Also in the Malheur, woodlands and subtropical shrublands are projected to expand greatly based on the "hot" GCM (HadGEM2-ES), but are projected to remain relatively stable based on the "wet" GCM (NORESM1-M). With all GCM's the temperate needleleaf forest contracts in the Malheur, suggesting that those forests are converting to other plant functional types.

An analysis of the plant functional type conversions between the historical period (1979–2008) and the end of the century (2070–2099) based on the "reference" GCM (CSIRO-Mk3.6.0) reveals greater details about the type shifts driven by climate change. Table 5 tallies the fractions of grid cells that shift from one plant functional type in the historical period to another plant functional type in by the end of the century. As stated earlier, some of the current plant functional types are highly unstable in these simulated projections. Sixty-nine percent of subalpine forest in the ecoregion convert to cool needleleaf forest by the end of the century, and 27% convert to temperate needleleaf forest (Table 5). A large fraction of existing cool needleleaf forest (82%) remains stable, but 15% of it degrades into the less productive temperate needleleaf woodland. Although much of the existing evergreen needleleaf forest remains stable (61%), a large fraction of it (32%) degrades into the less productive temperate needleleaf woodland. Dry temperate needleleaf forests are the least stable, and nearly all of them are projected to transition into less productive plant functional types, with 40% shifting into temperate needleleaf woodland, and 35% shifting into subtropical shrubland.

The dynamic mechanisms driving the forest conversions are

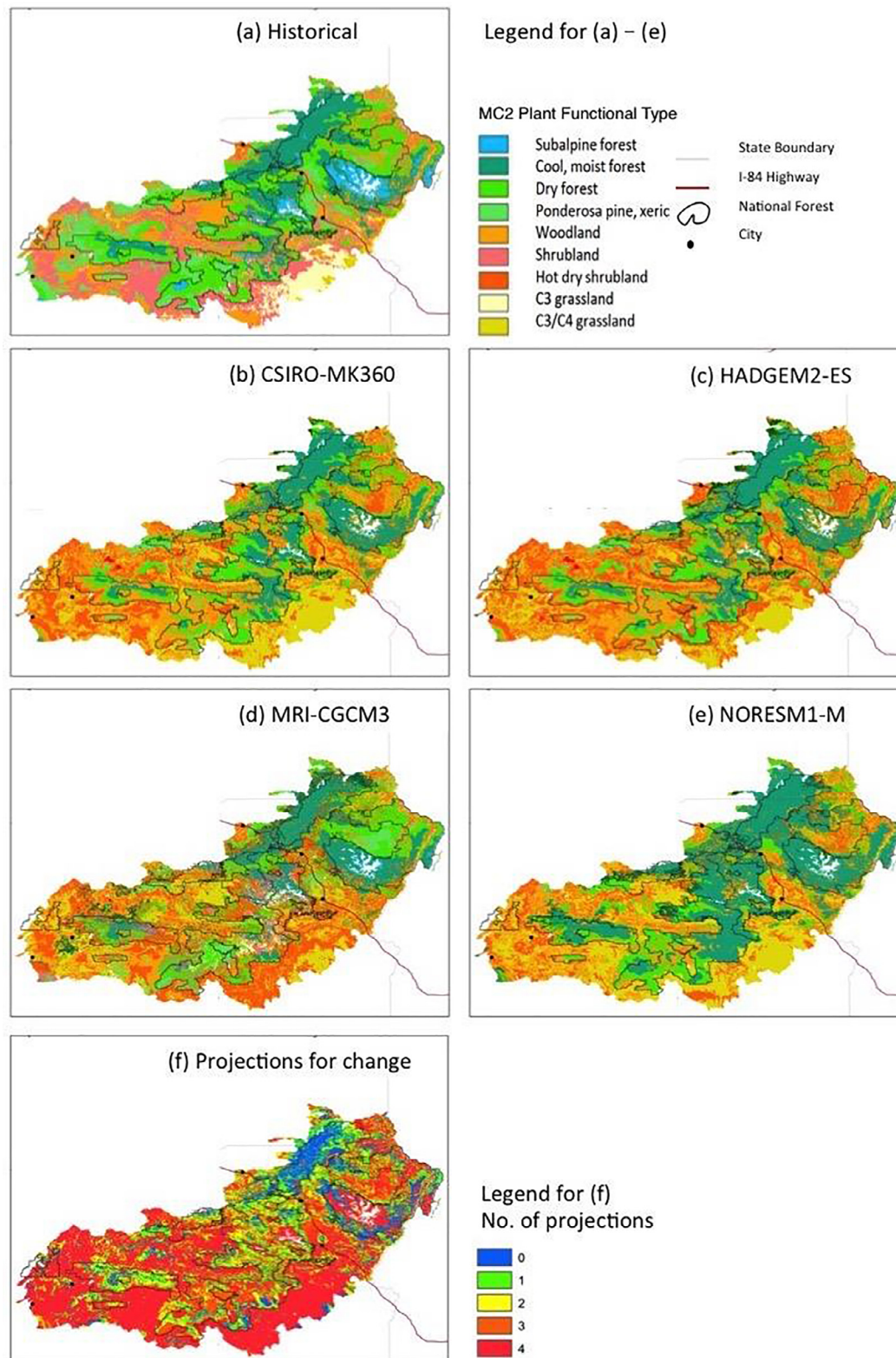


Fig. 7. Simulated vegetation distribution for 1979–2008 (a); projected distribution of MC2 plant functional type (PFT) for 2071–2100 under RCP8.5 climate change scenario for the four GCMs (b–e); and the number of future projections where vegetation is projected to change (f).

illustrated by the transient values of ecosystem characteristics (Fig. 9). Warming temperatures and increasing CO₂ concentrations steadily drive all biomes to higher levels of net primary productivity (NPP) throughout most of this century (Fig. 9a). Forest carbon stocks, however, decrease mid-century due to increased fire activity for three of the

four GCM's: the "reference" GCM (CSIRO-Mk3.6.0), the "hot" GCM (HadGEM2-ES), and the "wet" GCM (NORES M1-M) (Fig. 9c, d). For these three GCM's, fire occurrence was projected to increase nearly monotonically throughout the century (Fig. 9c), but burned areas peak mid-century and stabilize thereafter (Fig. 9d). The high levels of burned

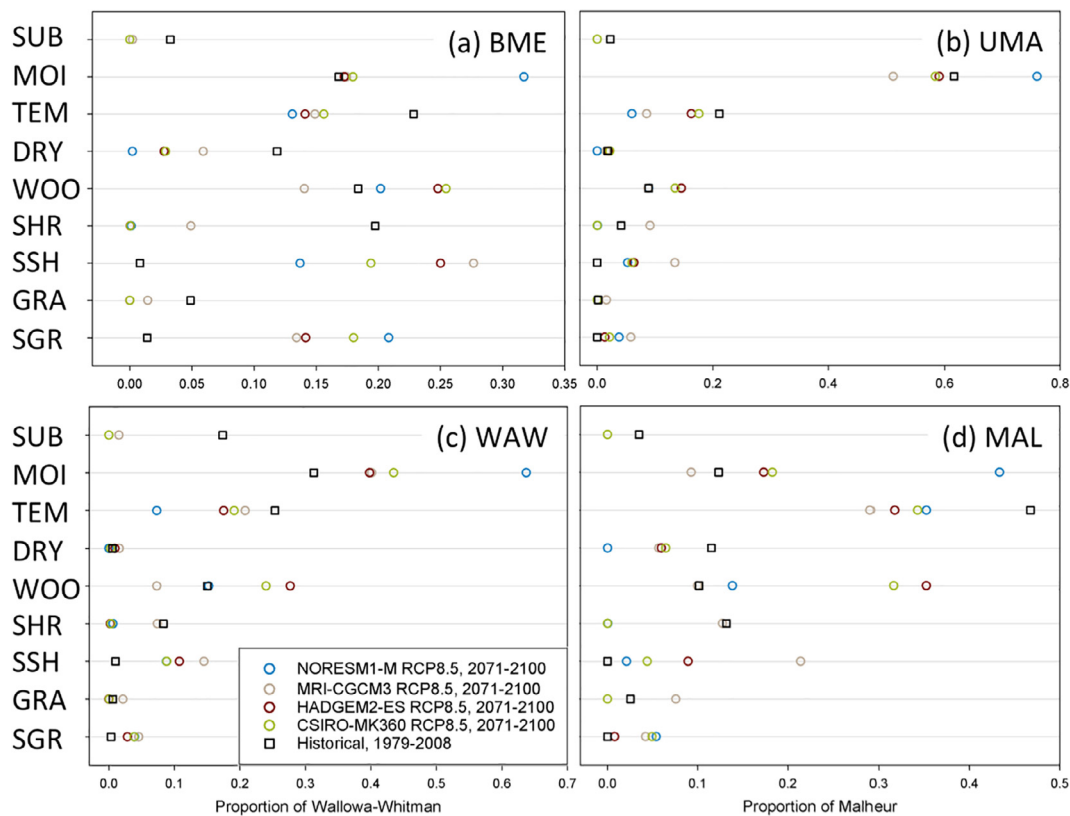


Fig. 8. Simulated proportions of MC2 PFT for the recent historical period (1979–2008) and the future (2071–2100) under RCP8.5 climate change scenario, aggregated for the Blue Mountains Ecoregion (BME) (a), Umatilla National Forest (UMA) (b), Wallowa-Whitman National Forest (WAW) (c), and the Malheur National Forest (MAL) (d). MC2 PFTs are abbreviated as follows: subalpine forest (SUB), moist temperate needleleaf forest (MOI), temperate needleleaf forest (TEM), dry temperate needleleaf forest (DRY), temperate needleleaf woodland (WOO), temperate shrubland (SHR), subtropical shrubland (SSH), temperate grassland (GRA), subtropical grassland (SGR).

areas in the mid-century catalyze major biome shifts during that time (Fig. 9e). With the “cool” GCM (MRI-CGCM3), there is a threshold effect where the projected increase in temperature does not result in a higher rate of fire occurrence until the very end of the century. Until then, warming temperatures and the CO₂ fertilization effect steadily increase net primary productivity and carbon accumulation in the forest. In the last decade of the century, fire occurrence increases, and the accumulated forest carbon stocks are burned.

4. Discussion

A dynamic global vegetation model (DGVM) designed and calibrated at the global or continental scales has difficulty representing finer-scale plant dynamics (Quillet et al., 2010), unless calibrated to regional conditions. In this paper we document a structured approach for calibrating MC2 DGVM to the Blue Mountains Ecoregion, where each major submodel of MC2 is calibrated to observation data (Fig. 4). This is a structured approach similar to one demonstrated for another terrestrial biome model, Biome-BGC (Wang et al., 2009), and an example, though a limited one, of the highly detailed and structured

Table 5

Plant functional type transitions for the Blue Mountains Ecoregion from historical (1979–2008) to end of the century (2070–2099) simulated with CSIRO-Mk3.6.0 under RCP8.5. The transition matrix shows the transition quantities as % of grid cells in historical plant functional types. Plant functional types that contribute less than 1% of landscape are omitted for clarity. Higher percentages are shaded darker. Matrix cells with black borderlines represent no transition.

	Moist Needleleaf Forest	Evergreen Needleleaf Forest	Dry Temperate Needleleaf Forest	Temperate Needleleaf Woodland	Subtropical Shrubland	Subtropical Grassland	No. Of Cells (% total)
Subalpine Forest	69%	2%		27%	2%		3,620 (3%)
Moist Ndlf Forest	82%	2%		15%	1%		18,659 (17%)
Evergreen Ndlf Forest	1%	61%	3%	32%	3%	0.1%	25,360 (23%)
Dry Temp Ndlf Forest		0.2%	14%	40%	35%	9%	13,160 (12%)
Temperate Ndlf Wdln	5%	4%	2%	25%	39%	26%	20,410 (18%)
Temperate Shrubland	4%	2%	1%	25%	33%	35%	21,929 (20%)
Temperate Grassland	2%	2%	1%	5%	3%	86%	5,429 (5%)
Subtropical Grassland		0.1%	0.2%	2%	22%	69%	1,553 (1%)
No. Of Cells (% total)	19,821 (18%)	17,334 (16%)	3,194 (3%)	28,276 (25%)	21,550 (19%)	19,998 (18%)	

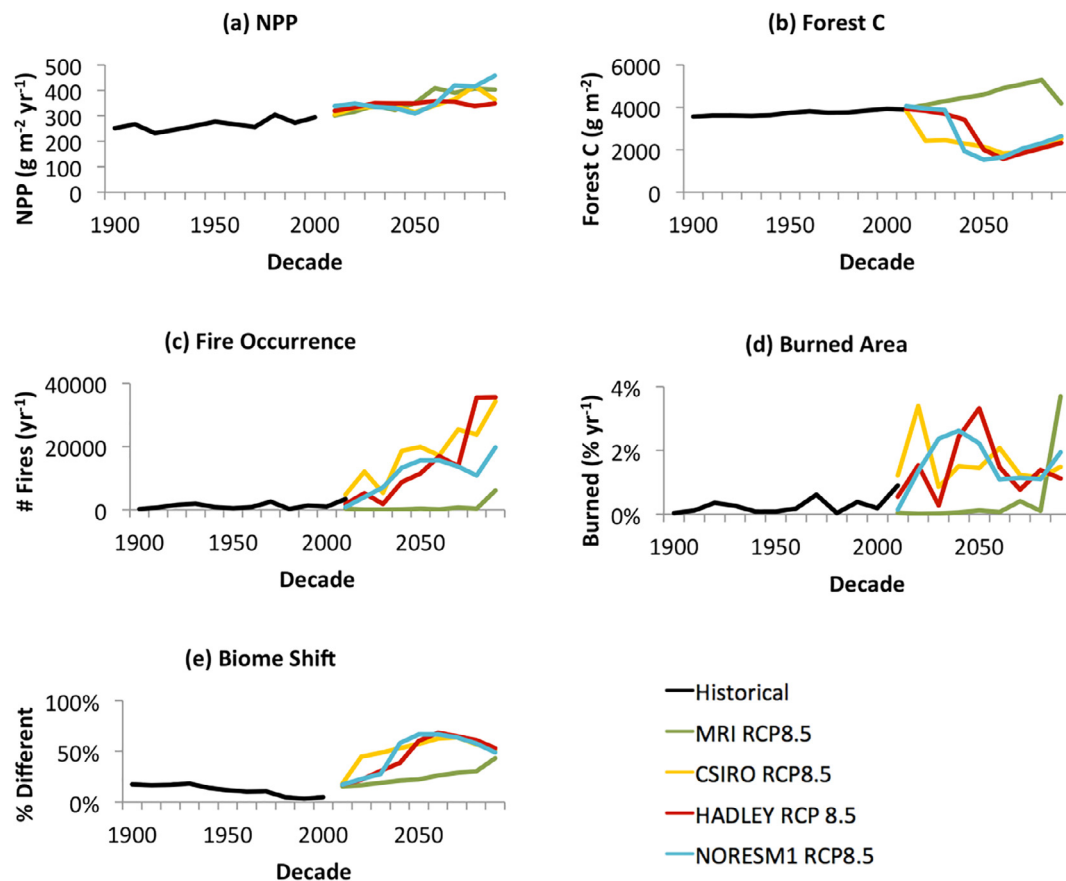


Fig. 9. Transient values of net primary productivity (NPP) (a), forest carbon stock (b), fire occurrence (c), area burned by fire (d), and changes in biome type (e). Values are averaged across the study area per year. Biome shift is calculated with respect to the 1979–2008 reference period.

approach advocated by Luo et al. (2012). Without a structured and balanced approach to calibration, the best possible fit may not be obtained, and may lead to over-fitting of inappropriate parameters.

As colorfully explained by Fisher et al. (2014), each DGVM is like a blind man describing an elephant. In addition, we believe each application of DGVM to a region has a set of strengths and limitations arising from the choice of climate datasets, simulation protocol, calibration, and model customizations. The current study is no exception, having several limitations. One shortcoming of our approach is that we did not calibrate the model to a larger simulation domain that includes areas that have historical climate that is analogous to future climate for the Blue Mountains Ecoregion. Identifying the climate analog areas and, if they occur where necessary input data may be obtained, calibrating the model to those areas would increase our confidence in model's ability to correctly simulate vegetation under possible future climates.

Another way to obtain a more robust set of future projections would be to use a greater ensemble of future climate datasets. Many high quality downscaled climate datasets had not been published when this study commenced but are now available: ClimateNA (Wang et al., 2012), NASA NEX-DCP30 (Thrasher et al., 2013), NARCCP (Mearns et al., 2009), and two datasets downscaled using the MACA method (Abatzoglou and Brown, 2012): MACA2-METDATA (Hegewisch and Abatzoglou, 2017a), and MACA2-LIVNEH (Hegewisch and Abatzoglou, 2017b). The use of these alternate climate dataset to drive MC2 simulations may yield significantly different projections.

Inaccurate soil data may have caused MC2 to inaccurately simulate most of the low-elevation areas between the Umatilla and Wallowa-Whitman National Forests as forests and shrublands, instead of grasslands. High resolution, high accuracy soil datasets are difficult to obtain for large study areas. Furthermore, the soil data format used by MC2, which represents only three soil layers, each with limited soil texture

information, may inadequately represent soil hydrologic, thermal and chemical traits. Additionally, the algorithm for nitrogen limitation was turned off in our simulations, due to the lack of satisfactory data to calibrate the process. Not coincidentally a survey of DGVM researchers show the word “nitrogen” as the most popular keyword in their description of research directions (Fisher et al., 2014).

MC2's fire submodel has important limitations. For one, it does not directly simulate the fire ignition process. Under climate change, lightning strikes are projected to increase (Romps et al., 2014), although it is unclear what the projections are for lightning *without* significant precipitation. Anthropogenic ignitions may also increase in the Blue Mountains, since recreation and tourism are significant activities in the region currently. Although climate change thus far has resulted in the perception of only milder winters, without the perception of uncomfortably hot summers, 88% of the U.S. population is projected to experience worsening weather in the future (Egan and Mullin, 2016), which may lead to immigration into this region and thereby increase anthropogenic ignitions. Another limitation related to fire simulation is that only a single fire return interval was prescribed per MC2 PFT, even though MC2 has the capacity to simulate a range of fire return intervals that respond to climate. At the commencement of the study, that mechanism had not been exercised and evaluated. Using it may increase simulated fire frequency, as the warming climate decreases the fire return intervals, which in turn expand the fraction of grid cell burned. Various efforts are underway to improve fire simulation in DGVMs (e.g., Pfeiffer and Kaplan, 2012), which may ultimately inform improvements to the MC2 fire submodel.

Other disturbances regimes were not simulated. Bachelet et al. (2015a) prescribed land use effects in their MC2 simulation of the conterminous U.S., and documented profound reductions on projections of carbon sequestrations and increases in forest expansion at the

continental scale, compared to simulations with no land use effects. The version of MC2 we used also does not simulate insect and pathogen outbreaks, invasive species, nor grazing on the understory vegetation.

All of the aforementioned limitations notwithstanding, our MC2 simulations made projections broadly consistent with projections made by MC2 in other applications. In all four of our projections there is near total loss of subalpine forests. Rogers et al. (2011) report the same projection for the loss of subalpine forests under the SRES A2 scenario for the Cascade Range, and Sheehan et al. (2015) report that subalpine forests are projected to be “nearly absent” under RCP8.5 in the “Eastern Northwest Mountains” region of the Pacific Northwest, which include the Blue Mountains Ecoregion. In our simulations, net primary production (NPP) increases throughout the century as temperatures increase, precipitation remains relatively stable, and CO₂ concentrations rise. This is due to the lengthening of the growing season, but the model does not constrain NPP for limited solar radiation under cloudy skies, which may be a significant factor in this region in the spring and fall (Rogers et al., 2011). Furthermore, MC2 does not directly simulate drought-induced carbon starvation and hydraulic failures, as well as other drought-induced paths to tree mortality (Zeppel et al., 2013), which may lead MC2 to overestimate productivity and survivorship by trees during the hotter future summers.

Our simulations project a steep increase in fire occurrence throughout the century and burned area peaking early- to mid-century, based on three out of the four GCMs used (Fig. 9). This is broadly consistent with the simulation results obtained by Sheehan et al. (2015) for the “Eastern Northwest Mountains” region of the Pacific Northwest, where they report a sharp reduction in mean fire return interval and a 40% increase in burned area from the 20th century to the 21st century. Rogers et al. (2011) also report fire activity intensifying in their simulation domain (which includes only the western half of the Blue Mountains Ecoregion) under the SRES A2 scenario. In our simulation, burned activity peaks mid-century for three of the four GCMs, coinciding with, and therefore likely driving, the reduction in forest C stocks and the peak in biome shifts (Fig. 9). This transient pattern is broadly consistent with the pattern reported by Bachelet et al. (2015a) for their continental U.S. simulations, where fire activity earlier in this century temporarily suppresses accumulation of vegetation carbon for 2–3 decades. The specific differences in simulated fire activity between our study and those by Bachelet et al. (2015a), Rogers et al. (2011) and Sheehan et al. (2015) arise from different fire calibrations, and the use of different climate scenarios and datasets.

In our simulations, the combined effect of increased NPP and fire activities in the future are that, while there are conversions between different coniferous forest types (Table 5), there is an overall 32.8% contraction of the coniferous forest from the historical period (1979–2008) to the end of the century (2070–2099). This is broadly consistent with conclusions from global scale studies, which note that temperate coniferous forests are vulnerable to climate change (Gonzalez et al., 2010), and that forest biomes will undergo pole-ward migration with the trailing edge converting to lower productivity biomes (Kim et al., 2017). Our projection of forest contraction, however, contradicts projections obtained by Sheehan et al. (2015), where forests in the Pacific Northwest expand despite increased fire activity. This difference underscores the conclusion by Rogers et al. (2011) that fire exerts a dominant control on the fate of the forests in the Pacific Northwest.

Some caution is advised when considering shifts between plant functional types. MC2 simulated wholesale conversions of temperate grasslands and shrublands to subtropical grasslands and shrublands. The underlying algorithm in MC2 uses only temperature thresholds. In this region, the invasion of subtropical species of grasses and shrubs may require a significant increase in summer precipitation (Pau et al., 2013), suggesting that MC2's representation of the conversions may be inaccurate. Similarly, MC2 used only annual precipitation values to distinguish among dry, mesic and moist needleleaf forests. These three

PFTs represent various species, including grand fir (*Abies grandis*), Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*), and their biogeography algorithm could be improved with insight from species distribution models.

Acknowledgements

We thank David Conklin at Common Futures LLC, for running some of the MC2 simulations. We thank Myrica McCune and Michelle Day at Oregon State University for pre-processing ILAP soils data. We thank David Rupp at Oregon Climate Change Research Institute (OCCRI) for creating Fig. 3. We thank Ayn Shlisky, Becky Gravenmier, Karen Bennett, and the Blue Mountains Restoration Strategy Interdisciplinary Team at the USDA Forest Service for consultations.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.cliser.2018.04.001>.

References

- Abatzoglou, J.T., Brown, T.J., 2012. A comparison of statistical downscaling methods suited for wildfire applications. *Int. J. Climatol.* <http://dx.doi.org/10.1002/joc.2312>.
- Abatzoglou, J.T., Rupp, D.E., Mote, P.W., 2014. Seasonal climate variability and change in the Pacific Northwest of the United States. *J. Clim.* 27 (5), 2125–2142.
- Bachelet, D., Ferschweiler, K., Sheehan, T., Stritholt, J., 2016. Climate change effects on southern California deserts. *J. Arid Environ.* 127, 17–29.
- Bachelet, D., Lenihan, J.M., Daly, C., Neilson, R.P., Ojima, D.S., Parton, W.J., 2001. MC1: a dynamic vegetation model for estimating the distribution of vegetation and associated carbon, nutrients, and water—technical documentation. Version 1.0. Gen. Tech. Rep. PNW-GTR-508. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. pp. 95.
- Bachelet, D., Ferschweiler, K., Sheehan, T.J., Sleeter, B.M., Zhu, Z., 2015a. Projected carbon stocks in the conterminous USA with land use and variable fire regimes. *Glob. Change Biol.* 21 (12), 4548–4560.
- Bachelet, D., Rogers, B.M., Conklin, D.R., 2015b. Challenges and limitations of using a DGVM for local to regional applications. In: *Global Vegetation Dynamics: Concepts and Applications in the MC1 Model*, pp. 31–40.
- Bell, D.M., Schlaepfer, D.R., 2016. On the dangers of model complexity without ecological justification in species distribution modeling. *Ecol. Model.* 330, 50–59.
- Beukema, S.J., Kurz, W.A., Pinkham, C.B., Milosheva, K., Frid, L., 2003. Vegetation Dynamics Development Tool User's Guide, Version 4.4c. Prepared by ESSA Technologies, Ltd., Vancouver, BC. pp. 239. Available at: <http://www.essa.com>.
- Cinquini, L., Crichton, D., Mattmann, C., Harney, J., Shipman, G., Wang, F., Ananthakrishnan, R., Miller, N., Denvil, S., Morgan, M., Pobre, Z., 2014. The earth system grid federation: an open infrastructure for access to distributed geospatial data. *Future Generation Comput. Syst.* 36, 400–417.
- Conklin, D.R., Lenihan, J.M., Bachelet, D., Neilson, R.P., Kim, J.B., 2016. MCFire model technical description. Gen. Tech. Rep. PNW-GTR-926. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.
- Creutzburg, M.F., Henderson, E.B., Conklin, D.R., 2015. Climate change and land management impact rangeland condition and sage-grouse habitat in southeastern Oregon. *AIMS Environ. Sci.* 2, 203–236.
- Daly, C., Bachelet, D., Lenihan, J.M., Neilson, R.P., Parton, W., Ojima, D., 2000. Dynamic simulation of tree-grass interactions for global change studies. *Ecol. Appl.* 10 (2), 449–469.
- Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *Int. J. Clim.* 28 (15), 2031–2064.
- Drapek, R.J., Kim, J.B., Neilson, R.P., 2015a. Continent-wide simulations of a dynamic global vegetation model over the United States and Canada under nine AR4 future scenarios. In: Bachelet, D., Turner, D. (Eds.), *Global Vegetation Dynamics: Concepts and Applications in the MC1 Model*. John Wiley & Sons, Inc, Hoboken, NJ. <http://dx.doi.org/10.1002/9781119011705.ch6>.
- Drapek, Raymond J., Kim, John B., Neilson, Ronald P., 2015b. The Dynamic General Vegetation Model MC1 over the United States and Canada at a 5-arcminute resolution: model inputs and outputs. Gen. Tech. Rep. PNW-GTR-904. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, pp. 57.
- Egan, P.J., Mullin, M., 2016. Recent improvement and projected worsening of weather in the United States. *Nature* 532 (7599), 357–360.
- Fisher, J.B., Huntzinger, D.N., Schwalm, C.R., Sitch, S., 2014. Modeling the terrestrial biosphere. *Annu. Rev. Environ. Resour.* 39, 91–123.
- Fowler, H.J., Blenkinsop, S., Tebaldi, C., 2007. Linking climate change modeling to impacts studies: recent advances in downscaling techniques for hydrological modeling. *Int. J. Climatol.* 27, 1547–1578.
- Gonzalez, P., Neilson, R.P., Lenihan, J.M., Drapek, R.J., 2010. Global patterns in the

- vulnerability of ecosystems to vegetation shifts due to climate change. *Glob. Ecol. Biogeogr.* 19 (6), 755–768.
- Halofsky, J.E., Creutzburg, M.K., Hemstrom, M.A. (Eds.), 2014a. Integrating social, economic, and ecological values across large landscapes. Gen.Tech. Rep. PNW-GTR-896. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, pp. 206.
- Halofsky, J.S., Halofsky, J.E., Burcsu, T., Hemstrom, M.A., 2014b. Dry forest resilience varies under simulated climate-management scenarios in a central Oregon, USA landscape. *Ecol. Appl.* 24 (8), 1908–1925.
- Halofsky, J.S., Halofsky, J.E., Hemstrom, M.A., Morzillo, A.T., Zhou, X., Donato, D.C., 2017. Divergent trends in ecosystem services under different climate-management futures in a fire-prone forest landscape. *Clim. Change* 142 (1–2), 83–95.
- Halofsky, J.E., Hemstrom, M.A., Conklin, D.R., Halofsky, J.S., Kerns, B.K., Bachelet, D., 2013. Assessing potential climate change effects on vegetation using a linked model approach. *Ecol. Model.* 266, 131–143.
- Halofsky, J.E., Peterson, D.L. (Eds.), 2016. Climate change vulnerability and adaptation in the Blue Mountains. Gen. Tech. Rep. PNW-GTR-939. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 331 p.
- Halofsky, J.E., Peterson, D.L., Marcinkowski, K.W., 2015. Climate Change Adaptation in United States Federal Natural Resource Science and Management Agencies: A Synthesis. U.S. Global Change Research Program, Washington, DC Available at: <http://www.globalchange.gov/browse/reports/climate-change-adaptation-united-states-federal-natural-resource-science-and>.
- Hann, W.J., Shlisky, A., Havlina, D., Schon, K., Barrett, S.W., DeMeo, T.E., Pohl, K., Menakis, J.P., Hamilton, D., Jones, J., Levesque, M., Frame, C.K., 2008. Interagency Fire Regime Condition Class (FRCC) guidebook. Version 1.3.0. pp. 119. Available at: <http://www.frcc.gov>.
- Hegewisch, K.C., Abatzoglou, J.T., 2017a. MACAv2-METDATA: Climate Model Outputs from CMIP5 using Multivariate Adaptive Constructed Analogs (MACA) v2 statistical downscaling method with METDATA Observational Training Dataset. USGS ScienceBase. Available at <http://climate.nkn.uidaho.edu/MACA/>. Accessed 08-05-2017.
- Hegewisch, K.C., Abatzoglou, J.T., 2017b. MACAv2-LIVNEH: Climate Model Outputs from CMIP5 using Multivariate Adaptive Constructed Analogs (MACA) v2 statistical downscaling 12 method with Livneh Observational Training Dataset. USGS ScienceBase. Available at <http://climate.nkn.uidaho.edu/MACA/>. Accessed 08-05-2017.
- Kerns, B.K., Kim, J.B., Kline, J.D., Day, M.A., 2016. US exposure to multiple landscape stressors and climate change. *Regional Environ. Change* 16 (7), 2129–2140.
- Kerns, Becky K., Powell, David C., Mellmann-Brown, Sabine, Carnwath, Gunnar, Kim, John B., 2017a. Chapter 6: Effects of climatic variability and change on upland vegetation in the Blue Mountains. In: Halofsky, Jessica E., Peterson, David L. (Eds.), Climate change vulnerability and adaptation in the Blue Mountains. Gen. Tech. Rep. PNW-GTR-939. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, pp. 149–250.
- Kerns, B.K., Powell, D.C., Mellmann-Brown, S., Carnwath, G., Kim, J.B., 2017b. Effects of projected climate change on vegetation in the Blue Mountains ecoregion, USA. *Clim. Serv.* <http://dx.doi.org/10.1016/j.cliser.2017.07.002>.
- Kim, J.B., Monier, E., Sohngen, B., Pitts, G.S., Drapek, R., McFarland, J., Ohrel, S., Cole, J., 2017. Assessing climate change impacts, benefits of mitigation, and uncertainties on major global forest regions under multiple socioeconomic and emissions scenarios. *Environ. Res. Lett.* 12 (4), 045001.
- King, D.A., Bachelet, D.M., Symstad, A.J., 2013. Climate change and fire effects on a prairie-woodland ecotone: projecting species range shifts with a dynamic global vegetation model. *Ecol. Evol.* 3 (15), 5076–5097.
- Loarie, S.R., Duffy, P.B., Hamilton, H., Asner, G.P., Field, C.B., Ackerly, D.D., 2009. The velocity of climate change. *Nature* 462 (7276), 1052.
- Luo, Y.Q., Randerson, J.T., Abramowitz, G., Bacour, C., Blyth, E., Carvalhais, N., Ciais, P., Dalmonech, D., Fisher, J.B., Fisher10, R., Friedlingstein11, P., 2012. A framework for benchmarking land models. *Biogeosciences* 9, 3857–3874.
- McDowell, N.G., Williams, A.P., Xu, C., Pockman, W.T., Dickman, L.T., Sevanto, S., Pangle, R., Limousin, J., Plaut, J., Mackay, D.S., Ogee, J., 2015. Multi-scale predictions of massive conifer mortality due to chronic temperature rise. *Nat. Clim. Change*.
- McKenzie, D., Peterson, D.W., Peterson, D.L., Thornton, P.E., 2003. Climatic and biophysical controls on conifer species distributions in mountain forests of Washington State, USA. *J. Biogeography*. 30, 1093–1108.
- Mearns, L.O., Gutowski, W.J., Jones, R., Leung, L.-Y., McGinnis, S., Nunes, A.M.B., Qian, Y., 2009. A regional climate change assessment program for North America. *EOS* 90, 311–312.
- Moser, S.C., Ekstrom, J.A., 2010. A framework to diagnose barriers to climate change adaptation. *Proc. Natl. Acad. Sci.* 107 (51), 22026–22031.
- Neilson, R.P., 1995. A model for predicting continental-scale vegetation distribution and water balance. *Ecol. Appl.* 5 (2), 362–385.
- Omerik, J.M., 1987. Ecoregions of the conterminous United States. *Ann. Assoc. Am. Geographers* 77 (1), 118–125.
- Parton, W.J., Scurlock, J.M.O., Ojima, D.S., Gilmanov, T.G., Scholes, R.J., Schimel, D.S., Kirchner, T., Menaui, J.C., Seastedt, T., Garcia, M.E., Kamnalrut, A., Kinyamario, J.I., 1993. Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. *Glob. Biogeochem. Cycles* 7, 785–809.
- Pau, S., Edwards, E.J., Still, C.J., 2013. Improving our understanding of environmental controls on the distribution of C3 and C4 grasses. *Glob. Change Biol.* 19 (1), 184–196.
- Peterman, W., Bachelet, D., Ferschweiler, K., Sheehan, T., 2014. Soil depth affects simulated carbon and water in the MC2 dynamic global vegetation model. *Ecol. Model.* 294, 84–93.
- Pfeiffer, M., Kaplan, J.O., 2012. SPITFIRE-2: an improved fire module for Dynamic Global Vegetation Models. *Geosci. Model Dev. Discuss.* 5 (2012), 2347–2443.
- Quillet, A., Peng, C., Garneau, M., 2010. Toward dynamic global vegetation models for simulating vegetation–climate interactions and feedbacks: recent developments, limitations, and future challenges. *Environ. Rev.* 18 (NA), 333–353.
- Rehfeldt, G.E., Crookston, N.L., Warwell, M.V., Evans, J.S., 2006. Empirical analyses of plant-climate relationships for the western United States. *Int. J. Plant Sci.* 167, 1123–1150.
- Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., Rafaj, P., 2011. RCP 8.5—A scenario of comparatively high greenhouse gas emissions. *Clim. Change* 109 (1–2), 33–57.
- Rogers, B.M., Neilson, R.P., Drapek, R., Lenihan, J.M., Wells, J.R., Bachelet, D., Law, B.E., 2011. Impacts of climate change on fire regimes and carbon stocks of the U.S. Pacific Northwest. *J. Geophys. Res.* 116, G03037. <http://dx.doi.org/10.1029/2011JG001695>.
- Romps, D.M., Seeley, J.T., Vollaro, D., Molinari, J., 2014. Projected increase in lightning strikes in the United States due to global warming. *Science* 346 (6211), 851–854.
- Rupp, D.E., Abatzoglou, J.T., Hegewisch, K.C., Mote, P.W., 2013. Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest USA. *J. Geophys. Res.: Atmos.* 118 (19).
- Rupp, D.E., Abatzoglou, J.T., Mote, P.W., 2016. Projections of 21st century climate of the Columbia River Basin. *Clim. Dyn.* 1–17.
- Sheehan, T., Bachelet, D., Ferschweiler, K., 2015. Projected major fire and vegetation changes in the Pacific Northwest of the conterminous United States under selected CMIP5 climate futures. *Ecol. Model.* 317, 16–29.
- Sitch, S., Huntingford, C., Gedney, N., Levy, P.E., Lomas, M., Piao, S.L., Betts, R., Ciais, P., Cox, P., Friedlingstein, P., Jones, C.D., 2008. Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs). *Glob. Change Biol.* 14 (9), 2015–2039.
- Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2016. Web Soil Survey. Available online at <https://websoilsurvey.nrcs.usda.gov/>. Accessed 2017-02-06.
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93 (4), 485–498.
- The Nature Conservancy, USDA Forest Service, and Department of the Interior, 2005. LANDFIRE Rapid Assessment Modeling Manual, Version 2.1. January 2005. Boulder, CO. pp. 72. Available at: <http://www.landfire.gov>. Accessed 2017-02-06.
- Thompson, M.P., Calkin, D.E., Finney, M.A., Ager, A.A., Gilbertson-Day, J.W., 2011. Integrated national-scale assessment of wildfire risk to human and ecological values. *Stoch. Env. Res. Risk Assess.* 25 (6), 761–780.
- Thorson, T.D., Bryce, S.A., Lammers, D.A., Woods, A.J., Omerik, J.M., Kagan, J., Pater, D.E., Comstock, J.A., 2003. Ecoregions of Oregon (color poster with map, descriptive text, summary tables, and photographs): Reston, Virginia, U.S. Geological Survey (map scale 1:1,500,000).
- Thrasher, B., Xiong, J., Wang, W., Melton, F., Michaelis, A., Nemani, R., 2013. Downscaled climate projections suitable for resource management. *Eos, Trans. Am. Geophys. Union* 94 (37), 321–323.
- Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.F., Masui, T., 2011. The representative concentration pathways: an overview. *Clim. Change* 109 (1–2), 5.
- Van Wagoner, C.E., 1987. Development and structure of the Canadian Forest Fire Weather Index System. *Forestry Tech. Rep.* 35. Ottawa, Canada: Canadian Forestry Service. pp. 35. <https://cfs.nrcan.gc.ca/publications?id=19927>.
- Wang, T., Hamann, A., Spittlehouse, D.L., Murdock, T.Q., 2012. ClimateWNA-High-resolution spatial climate data for western North America. *J. Appl. Meteor. Climatol.* 51, 16–29.
- Wang, W., Ichii, K., Hashimoto, H., Michaelis, A.R., Thornton, P.E., Law, B.E., Nemani, R.R., 2009. A hierarchical analysis of terrestrial ecosystem model Biome-BGC: equilibrium analysis and model calibration. *Ecol. Model.* 220 (17).
- Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western U.S. forest wildfire activity. *Science* 313, 940–943.
- Yospin, G.I., Bridgman, S.D., Neilson, R.P., et al., 2015. A new model to simulate climate change impacts on forest succession for local land management. *Ecol. Appl.* 25, 226–242.
- Zeppel, M.J., Anderegg, W.R., Adams, H.D., 2013. Forest mortality due to drought: latest insights, evidence and unresolved questions on physiological pathways and consequences of tree death. *New Phytol.* 197 (2), 372–374.
- Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W., 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sens. Environ.* 95, 164–176.