Forest Ecology and Management 477 (2020) 118498

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Bioclimatic modeling of potential vegetation types as an alternative to species distribution models for projecting plant species shifts under changing climates

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ARTICLE INFO

Keywords:
Statistical modeling
Habitat types
Random forests
Constancy
Climate offsets
WXFIRE

ABSTRACT

Land managers need new tools for planning novel futures due to climate change. Species distribution modeling (SDM) has been used extensively to predict future distributions of species under different climates, but their map products are often too coarse for fine-scale operational use. In this study we developed a flexible, efficient, and robust method for mapping current and future distributions and abundances of vegetation species and communities at the fine spatial resolutions that are germane to land management. First, we mapped Potential Vegetation Types (PVTs) using conventional statistical modeling techniques (Random Forests) that used bioclimatic ecosystem process and climate variables as predictors. We obtained over 50% accuracy across 13 mapped PVTs for our study area. We then applied future climate projections as climate input to the Random Forest model to generate future PVT maps, and used field data describing the occurrence of tree and non-tree species in each PVT category to model and map species distribution for current and future climate. These maps were then compared to two previous SDM mapping efforts with over 80% agreement and equivalent accuracy. Because PVTs represent the biophysical potential of the landscape to support vegetation communities as opposed to the vegetation that currently exists, they can be readily linked to climate forecasts and correlated with other, climate-sensitive ecological processes significant in land management, such as fire regimes and site productivity.

1. Introduction

The influence of past climate variability in shaping today's environments has been largely overwhelmed by contemporary anthropogenic drivers of land use and changes in global climate that are unprecedented over past millennial time scales (Cook et al., 2016). Climate change is widely recognized as the largest threat to biodiversity, species survival, and ecosystem integrity across most biomes (Thuiller et al., 2008, Maclean and Wilson, 2011). Anthropogenic climate change and associated impacts are a leading and widespread causes of the emergence of novel species assemblages, species range shifts, local extinctions, reduced biodiversity, loss of ecosystem

Acronyms: ABLA, Subalpine fir (*Abies lasiocarpa*); BCMPVT, Name of this modeling effort BioClimatic Modeling of Potential Vegetation Types; BPS, Biophysical settings as used in LANDFIRE; CanESM2, Climate scenario developed from the CanESM2 GCM; CLUN, Queencup beadlily (*Clintonia uniflora*); CNRM-CM5, Climate scenario developed from the CNRM-CM5 2 GCM global climate model; DAYMET, a 1 km resolution daily climate grid used to simulate climate; ECODATA, An ecological monitoring and inventory system used to collect some field data in this project; FIA, Forest Inventory and Analysis, A US Forest Service program that collected the majority of field data used in this project; FSVeg, A US Forest Service standardized inventory system that was used to collect some data in this study; GCM, Global Circulation Models; HadGEM2-ES, Climate scenario developed from the Hadley HADGEM2-ES summary; LANDFIRE, A national effort to map ecological characteristics at fine scales; LAOC, Western larch (*Larix occidentalis)*; LIBO, Twinflower (*Linnea borealis*); MEFE, Menziesia (*Menziesia ferruginea*); NEX-DCP30, the NASA Earth Exchange Downscaled Climate Projections dataset; NRCS, National Resource Conservation Service, a part of US Dept. Agriculture; PIAL, Whitebark pine (*Pinus albicaulis*); PSME, Douglasfir (*Pseudotsuga menziesii*); PIPO, Ponderosa pine (*Pinus pondersa*); PVT, Potential Vegetation Type (habitat type); RF, Random Forests, a statistical method used to create the models in this effort; SDM, Species distribution models; SDM-F, Species distribution model created by the FORECASTS project; SDM-M, Species distribution models created by the US Forest Service Moscow Laboratory; SWCC, SouthWest Crown of the Continent, the study area; THPL, western redcedar (*Thuja plicata*); VASC, Grouse whortleberry (*Vaccinium scoparium*); WXFIRE, A spatial model used to downscale DAYMET 1 km data to 30 m pixels; XETE, Beargrass (*Xerophyllum tenax*)

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https://doi.org/10.1016/j.foreco.2020.118498
Received 2 April 2020; Received in revised form 13 July 2020; Accepted 8 August 2020

resilience, and altered disturbance regimes of a magnitude not previously observed (Chen et al., 2011, Abatzoglou and Williams, 2016, Franklin et al., 2016, Stevens-Rumann et al., 2018). Globally, species distributions have shifted to higher elevations at a median rate of 11.0 m per decade, and to higher latitudes at a median rate of 16.9 km per decade (Chen et al., 2011). Future changes in species distributions depend upon the rate, magnitude, and direction of ongoing changes in global climate drivers and their local expressions, and upon other biological factors, such as the extent and limits of populations' adaptation to ongoing climate change, characteristics of biotic interactions across trophic levels, disturbances and their amplification, and human land use and management (Jackson et al., 2009, Krawchuk et al., 2009, Lavergne et al., 2010, Van Der Putten et al., 2010, Bürgi et al., 2017).

Developing effective management strategies and tools in the context of changing climate and disturbance regimes is a central challenge in natural resource planning (Milad et al., 2011, Falk, 2013). Emerging environments that fall outside known historical ranges hinder our ability to develop prescient views of future conditions and change (Currie, 2001, Seastedt et al., 2008). The capacity of conservation and management practices to respond to climate change relies on our skill at predicting climate trajectories in coming decades, coupled with our ability to predict ecological and biogeographic responses to that climate change, as well as the effects of future land management practices (Heller and Zavaleta, 2009, Jackson et al., 2009, Colavito, 2017). Potential emergence of novel ecosystem patterns and processes suggests that the valuable information and data gained from past studies may need to be interpreted in new climate contexts; new, creative approaches are needed to create the necessary tools for managing tomorrow's landscapes (Gustafson, 2013). Because past empirical studies and the accrued wisdom of the last century may incompletely inform management strategies for tomorrow's landscapes, statistical and simulation models have become critical tools for guiding management decisions in an era of rapid change (Loehman et al., 2020).

Species Distribution Models (SDM), also called species niche models, bio-envelope models, or species envelope models, have been used extensively to predict species responses under various climate change projections (Gill, 1997, Iverson and Prasad, 1998, Guisan and Zimmermann, 2000, Shafer et al., 2001, Rehfeldt et al., 2012, Chang et al., 2014). SDMs are developed by associating contemporary climate data with species' current distributions using advanced statistical modeling (Thuiller, 2003); for example, various climate variables estimated for locations where a species is known to exist are correlated to species presence and that relationship is then used to map species distribution across a broad spatial domain (Guisan and Zimmermann, 2000, Iverson and McKenzie, 2013). Future species distributions are then estimated for that domain using projected future climate data as inputs to the statistical model (Guisan and Zimmermann, 2000, Watling et al., 2012, Franklin, 2013). SDMs have been used to model past and future distributions of many species, including butterflies (Vanhanen et al., 2007), reptiles and amphibians (Wright et al., 2016), and trees (Iverson and Prasad, 1998). These future projections have been used in land management to evaluate species vulnerability and resilience under changing climates (Mellert et al., 2015, Pecchi et al., 2019).

Most SDM products, especially for those species actively managed by public agencies, have major limitations. Often, spatial distribution information for many species of management concern are not widely available, especially for exotic, forage, and endangered species. Also, generating the data layers needed for SDM map creation may be too complicated or costly for public land management agencies, especially for rare or endemic species which have limited demographic data. Many SDM maps are often based on species presence or absence and do not incorporate species abundance, an important variable in land management. Some SDM data layers have resolutions that are too coarse (> 1 km pixel size) for planning land management activities, which are often implemented at the scale of individual stands or watersheds (Brown et al., 2004, Keane et al., 2018a). Moreover, because SDM are based on single species distributions, projected distributions cannot be combined to reflect changes in vegetation communities, as are often required for many land management tasks including grazing allocation estimates, wildlife habitat evaluations, or cover type mapping. Last and most importantly, interpretation of and inferences from SDM projections are subject to biases that must be considered in the planning process, including:

1. Insufficient plot data to fully describe the range of a species (Hallman and Robinson, 2020);
2. Species absence from a plot for reasons other than climate, such as disturbance, shade-tolerance, or exotic competition (Thuiller et al., 2008, Adler et al., 2014, Pecchi et al., 2019); and
3. Seedling establishment facilitated by microclimate rather than macroclimate (Whitbeck et al., 2016).

Potential Vegetation Type (PVT) classifications have been used extensively in land management over the last 60 years, especially across the western United States (Mueller-Dombois, 1964, Arno and Pfister, 1977, Emmingham et al., 1980, Pfister and Arno, 1980, Alexander, 1988) and western Canada (Sivak, 1987). PVT classifications have many names depending on scale and application, including habitat types (Pfister et al., 1977), plant associations (Henderson et al., 1989), biophysical settings (Rollins, 2009), and potential natural vegetation (Kuchler, 1975, McArthur and Ott, 1995). The theory behind most PVT classifications is that the vegetation community that would develop over long time periods in the absence of disturbance (i.e., near-climax vegetation) provides a basis for identifying unique biophysical site conditions (Daubenmire, 1966). Because PVTs indicate ecological site potential, they have also been used to describe and map many other important ecological processes, such as successional development (Arno et al., 1985, Keane et al., 2006), fire regimes (Barrett, 1988, Morgan et al., 2001), and site productivity (Stage, 1975, Milner, 1992). PVTs have been the backbone of many successful public land planning projects over the last 50 years (Pfister, 1980) specifically because they represent what may occur (e.g. potential vegetation), as opposed to what currently exists (e.g. existing vegetation), on a site. However, to date, PVTs have not been used as a tool for anticipating changing ecosystems and landscapes under climate change.

Most PVT classifications use indicator species to key to a specific class or sub-category of vegetation communities (Daubenmire, 1966). Tree species' shade tolerance, for example, is critical for selecting the first level of indicator species in many forest PVT classifications; the most shade tolerant tree species that will eventually become dominant on the site in the absence of disturbance can be used to uniquely identify the coarsest categories in the classification. Along with the presence of tree species, the occurrence of various other indicator species in the undergrowth allows for classification into finer ecological levels (Pfister and Arno, 1980). Because all PVT classifications have a key to identify classes, managers can easily identify unique biophysical conditions from species composition and cover observed in the field or from legacy plot data (Smith and Fischer, 1997). However, the great genetic diversity and varied disturbance impacts on indicator species often serve to widen the ecotones between PVT classes making identification sometimes difficult (Arno and Pfister, 1977, Pfister and Arno, 1980).

Using statistical methods similar to SDM approaches, maps of PVT classifications have been created to aid in numerous land management activities using bioclimatic modeling (BCM) (Deitschman, 1973, Keane et al., 2000, Rollins et al., 2004, Rollins, 2009). In this method, PVT classes, keyed from vegetation plot data, are correlated with spatially explicit climate, ecological process, and topographical variables (Rollins et al., 2004, Holsinger et al., 2006). Early mapping efforts, such as in Deitschman (1973), used topographic settings defined by aspect, slope, and elevation, along with soils information, to aid in mapping PVTs. Later efforts, such as the LANDFIRE project, mapped PVTs (called

Biophysical Settings or BPSs) across the U.S. by relating each BPS with climate and ecosystem productivity variables (Rollins et al., 2004, Holsinger et al., 2006, Rollins, 2009).

Given the extensive practice of using PVTs in public land management and the high fidelity of PVTs to unique biophysical conditions, we suggest that prediction of future PVTs may be useful for integrating climate change impacts into land management planning efforts (Pfister, 1980). Such PVT maps provide a high-resolution, ecologically consistent, and robust tool — greatly needed for addressing a diversity of land management concerns. In this study, we used BCM (bioclimatic modeling) methods to map PVT spatial distributions (hereafter called BCMPVT method) across a large landscape under four climate scenarios (current climate and three future projections). We then mapped individual plant species distributions using the PVT maps; that is, species presence data were linked to each mapped PVT class to predict where individual species may occur in the present and future. We recognize that both SDM and BCMPVT approaches have major limitations for use in fine-scale management projects, but we feel that future PVT maps may be more useful and robust to land management because they may be used for many other management challenges, such as mapping fuels (Keane et al., 1998), simulating vegetation development (Chew, 1997, Keane et al., 2006), and classifying fire regimes (Morgan et al., 1996, Barrett, 2004).

This study has five main objectives that build on each other: (1) develop a statistical method for mapping PVTs using climate and simulated ecosystem variables; (2) create maps of current and three possible future PVTs using Random Forest classification techniques; (3) create maps of current and future plant species distributions from PVT maps using species abundance field data sampled by Pfister et al. (1977); (4) estimate accuracies of the PVT and SDM species maps; and (5) compare current and future species distributions derived from PVT mapping with those predicted from two previous SDM mapping efforts. The mapping of PVTs in this study was accomplished using a generalized approach that employed only variables derived from climate data to keep it simple, but our method could easily be expanded by integrating other variables, such as satellite imagery, topography, and soils information, into the analysis. The primary goal of this paper is to develop a faster, less costly, and more useful alternative method (Fig. S.1) for mapping future projections of species and ecosystem characteristics for natural resource management.

2. Methods

2.1. Study area

Our modeling domain was the Southwest Crown of the Continent (SWCC), a 519,322 ha landscape in west-central Montana, USA (Fig. 1). Current vegetation communities within the SWCC are comprised of ponderosa pine (*Pinus ponderosa* P. Lawson & C. Lawson) and Douglas-fir (*Pseudotsuga menziesii* var. *glauca* (Mayr) Franco) -dominated forests (~50% of forested landscape) in drier, lower elevations; Douglas-fir and subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.) dominated forests with seral lodgepole pine (*Pinus contorta* var. *contorta Douglas ex Loudon*) stands (~30% of forested landscape) at middle elevations, and subalpine fir, Engelmann spruce (*Picea engelmannii Parry ex Engelm.*) with successional lodgepole pine and whitebark pine (*Pinus albicaulis Engelm.*) dominated forests (~20% of forested landscape) at upper elevations (Fig. 1b). The valley floor areas are dominated by seral subalpine fir, western redcedar (*Thuja plicata* Donn ex D.Don) and Engelmann spruce with an abundance of frost pockets (Arno 1979). Rainfall ranges from over 1500 mm at high elevations (over 2,500 masl) to under 250 mm at the lowest elevations (around 1,200 masl). Average slope is over 35 percent and aspects are well distributed across all cardinal directions. Climate is mostly maritime with weather systems originating in the west (Arno, 1979). We divided the study domain into ~ 10 to 100 ha polygons using forest stand maps available from the U.S. Forest Service for both ease of mapping and replicating standard land management analysis approaches.

2.2. Data sources

2.2.1. Plot data

We used the Pfister et al. (1977) forested habitat types of Montana, USA as our PVT classification (Table 1). This classification has three levels that uniquely identify biophysical conditions: series, habitat type, and phase. At field settings, series is selected based on the most shade-tolerant tree species on in the sampling frame. The habitat type level is selected based on an ordered listing of indicator undergrowth plant species and their minimum cover thresholds, which are used to identify unique vegetation assemblages and biophysical conditions within the broader series (tree) level. Phases, the third level, are keyed from additional indicator undergrowth species to further identify finer levels within a habitat type. Some habitat types do not have phases, while other habitat types have as many as five phases. In this study, we grouped habitat types and phases together if there were insufficient field data to accurately map them (Fischer and Bradley, 1987). We ultimately modeled a set of 13 habitat types (Table 1).

Georeferenced field data that contained plot-based identification of the habitat type (PVT) came from several sources. We first queried the U.S. Forest Service Forest Inventory and Analysis (FIA) database (https://www.fia.fs.fed.us/) for all plots in the study area and obtained the PVT information needed for modeling these plots through coordination with the FIA program (459 plots). Next, we obtained the ECODATA ecological inventory legacy plots from the Northern Region of the U.S. Forest Service and extracted those georeferenced plots with PVT assignments within our study area (572 plots) (Jensen et al., 1993, Keane et al., 2002). Last, we obtained stand-level data collected using Field Sampled Vegetation (FSVeg; http://www.fs.fed.us/nrm/fsveg/) methods where PVT was identified (USDA Forest Service 2019) and used the centroid of each stand as the plot location (1,198 plots). All compiled data contained field determinations of PVT to the habitat type phase level. FIA and ECODATA plots also contained field evaluations of abundance (presence) for major plant species used in this study.

2.2.2. Climate data

Contemporary climate data was sourced from DAYMET (Thornton et al., 2012) distributed by the Oak Ridge National Laboratory Distributed Active Archive Center (http://daymet.ornl.gov/). The DAYMET data included minimum and maximum temperature, precipitation, solar radiation, vapor pressure and day length at daily timesteps for the years 1980 to 2017. Future climate data were obtained from the NASA Earth Exchange Downscaled Climate Projections (NEX-DCP30) dataset, which includes high-resolution, bias-corrected monthly averaged maximum and minimum near-surface temperature and precipitation at 30 arc-second resolution (Thrasher et al., 2013) (URL: https://cds.nccs.nasa.gov/nex/). These data were derived from three General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5; (Taylor et al., 2012) for the Representative Concentration Pathway (RCP) 8.5 (Meinshausen et al., 2011), a "business as usual" scenario wherein no societal efforts are made to reduce greenhouse gas emissions. We selected the CanESM2 and CNRM-CM5GCMs models based on their superior performance in the western U.S. (Rupp et al., 2013) and the HadGEM2-ES GCM for its similarity to GCMs used in the comparative SDM products. For our primary analyses we used the HadGEM2-ES RCP 8.5 scenario but we report on the full complement of GCM results in the Supplementary Material.

2.2.3. Biophysical gradient data

The spatial climate layers used to predict current and future PVTs were created using the WXFIRE program (Keane and Holsinger, 2006, Keane et al., 2007), a biophysical simulation model, that integrates

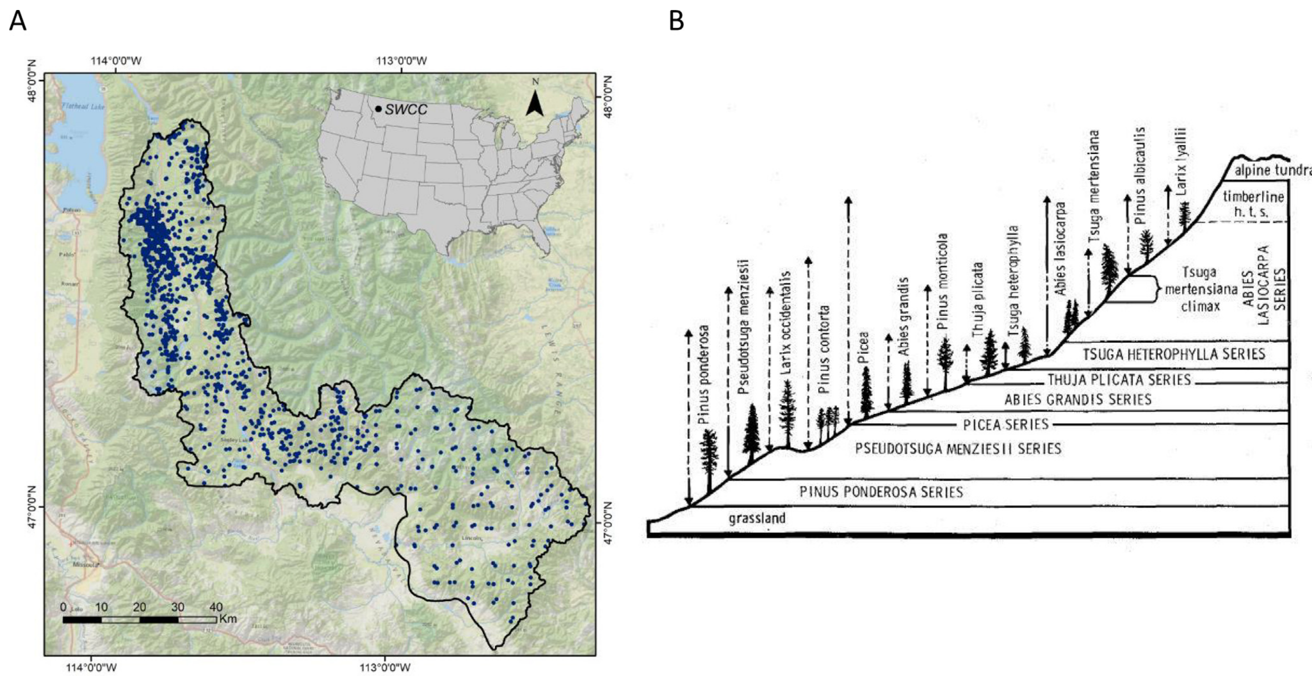

Fig. 1. The Southwest Crown of the Continent (SWCC) study area and the elevational range of habitats. (A) The SWCC is a large landscape (519,322 ha) consisting of a wide valley bounded by high mountain ranges, the Mission Mountains to the west and the Swan Mountains to the east. Blue dots are field data locations in the SWCC. (B) Distribution of tree species and habitat type series along an elevational gradient. The lower elevation habitats are typically drier and warmer and precipitation increases and temperature decreases with elevation. The most productive series are in the valley bottoms and mid-slopes (Abies grandis, Thuja plicata). From _ENREF_82Pfister et al. (1977). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
The PVT classes (habitat type groupings) used in this study. These classes were synthesized from the habitat types in the Pfister et al. (1977) classification. The habitat type acronym is the reference name used throughout this paper. The reference phase was used to obtain individual species presence or absence from the constancy and average cover tables in Pfister et al. (1977) Appendix C. Some phases had so few plots that we grouped them up to the habitat type level (Grouping column).

Habitat type acronym	Habitat type common name	Phases grouped within each habitat type	Plots (n)
ABGR/CLUN	Grand fir/queencup beadlily	***Abies grandis/Clintonia uniflora-Aralia nudicaulis- Xerophyllum tenax***	124
		Abies grandis/Clintonia uniflora-Clintonia uniflora	
ABLA/CLUN-CLUN	Subalpine fir/queencup beadlily	***Abies lasiocarpa/Clintonia uniflora-Clintonia uniflora***	258
ABLA/CLUN-VACA	Subalpine fir/queencup beadlily, dwarf huckleberry phase	***Abies lasiocarpa/Clintonia uniflora-Vaccinium caespitosum***	374
ABLA/LIBO	Subalpine fir/twinflower	***Abies lasiocarpa/Linnaea borealis-Xerophyllum tenax***	45
		Abies lasiocarpa/Linnaea borealis-Linnaea borealis	
		Abies lasiocarpa/Linnaea borealis-Vaccinium scoparium	
ABLA/LUHI	Subalpine fir/smooth woodrush	***Abies lasiocarpa/Luzula hitchcockii-Vaccinium scoparium***	99
		Abies lasiocarpa/Luzula hitchcockii-Menziesia ferruginea	
		Abies lasiocarpa/Luzula hitchcockii-Vaccinium scoparium	
ABLA/MEFE	Subalpine fir/menzesia	***Abies lasiocarpa/Menziesia ferruginea***	172
ABLA/XETE	Subalpine fir/beargrass	***Abies lasiocarpa/Xerophyllum tenax-Vaccinium globulare***	189
		Abies lasiocarpa/Xerophyllum tenax-Vaccinium membranaceum	
		Abies lasiocarpa/Xerophyllum tenax-Vaccinium scoparium	
PIAL-ABLA	Whitebark pine/subalpine fir	***Pinus albicaulis-Abies lasiocarpa***	28
PICEA/CLUN	Spruce/queencup beadlily	***Picea/Clintonia uniflora-Clintonia uniflora***	62
PSME/PHMA	Douglas-fir/ninebark	***Pseudotsuga menziesii/Physocarpus malvaceus-Physocarpus malvaceus***	70
		Pseudotsuga menziesii/Physocarpus malvaceus-Calamagrostis rubescens	
PSME/SYAL	Douglas-fir/snowberry	***Pseudotsuga menziesii/Symphoricarpos albus-Calamagrostis rubescens***	67
		Pseudotsuga menziesii/Symphoricarpos albus-Symphoricarpos albus	
PSME/VACA	Douglas-fir/dwarf huckleberry	***Pseudotsuga menziesii/Vaccinium caespitosum***	128
		Pseudotsuga menziesii/Vaccinium membranaceum	
		Pseudotsuga menziesii/Vaccinium membranaceum-Vaccinium membranaceum	
		Pseudotsuga menziesii/Vaccinium membranaceum-Arctostaphylos uva-ursi	
		Pseudotsuga menziesii/Vaccinium membranaceum-Xerophyllum tenax	
THPL/CLUN	Western redcedar/queencup beadlily	***Thuja plicata/Clintonia uniflora-Clintonia uniflora***	613
		Thuja plicata/Clintonia uniflora-Aralia nudicaulis	
		Thuja plicata/Clintonia uniflora-Menziesia ferruginea	

DAYMET climate data (Thornton et al., 2012) with topographic data (elevation, aspect, slope), soils data (composition and depth derived from the USDA-NRCS Soil Survey Geographic or SSURGO dataset), leaf area index (derived from MODIS reflectance data), and ecophysiological site data (derived from LANDFIRE biophysical settings data) (Rollins, 2009) to compute climatic and biophysical gradients across our study area (Keane and Holsinger, 2006). We used WXFIRE to (1) downscale the coarse 1 km DAYMET data to 30 m resolution in complex topography using biophysical extrapolation, (2) simulate ecological processes using the downscaled weather data, and (3) summarize scaled weather and ecological simulation results to annual averages for a diverse set of climate descriptors (Keane and Holsinger, 2006).

To produce future biophysical gradient layers, we adjusted the current DAYMET weather using temperature, precipitation, and $C0_2$ level offsets derived from the downscaled NEX-DCP30 projections (Keane et al., 2019). Temperature offsets were calculated as the absolute difference between the current and projected future conditions by season and GCM, and precipitation offsets were calculated as percent changes between time periods by season and GCM. The WXFIRE model generated 51 spatially explicit maps of climate and ecosystem variables (see Keane and Holsinger (2006) for a full list) for both current and future projected climate conditions.

2.3. Modeling current and future PVTs

We used the Random Forest (RF) machine learning algorithm (Breiman 2001) implemented in R (R Development Core Team 2020) with the RF package 4.6–14 (Liaw and Wiener, 2002) to predict current and future PVT distributions. Training and validation data were extracted at plot locations from WXFIRE biophysical gradients modeled under contemporary climate. The RF model predicted current PVT for the study domain from these simulated variables. First, we identified the most important, uncorrelated predictors (20 of the 51 possible variables) (Table 2) for the model by calculating measures of variable importance estimated by comparing how prediction error increases when data for one variable is permuted while all others are left unchanged (Cutler et al., 2007) using the Caret package for R (Kuhn, 2008). Next, we determined "tuning" parameters in the RF algorithm by implementing repeated *k*-fold cross-validation procedures on a 70% subsample (i.e. training data) of our SWCC dataset. Resulting parameter values were the number of classification trees (500), number of variables to split at each node (12), and the node size (2). We assessed model accuracy on the remaining 30% of the data set withheld from the RF training effort, and measured overall percentage of PVTs correctly classified (contingency table), as well as kappa - amount of agreement between predicted vs actual corrected for chance alone (Cutler et al., 2007).

This RF model was then used to predict future distributions of PVT classes across the study area. Here, we used the biophysical gradient

Table 2
Predictor variables used for modeling PVTs (habitat types) in the order of importance in the Random Forests (RF) modeling.

Name	Units
Vapor Pressure Deficit	index
Minimum daily temperature	°C
Total solar radiation	kJ m^{-2} day^{-1}
Maximum daily temperature	°C
Nighttime daily temperature	°C
Photon flux density	Umol m^{-2}
Solar radiation flux to the ground	K
NFDRS Spread Component (SC)	kW m^{-2} day^{-1}
Relative humidity	%
Average daily temperature	°C
Soil temperature	°C
Moisture content of herbaceous fuel	°C
NFDRS Energy Release Component (ERC)	index
NFDRS Burning Index (BI)	Index
Evaporation	kg H2O yr^{-1}
Degree-days	day °C
Moisture content of 100-hour fuel	%
NFDRS ignition component (IC)	index
Potential evapotranspiration	kg H2O yr^{-1}
Surface area weighted reaction intensity (IR)	Index

layers produced by WXFIRE under future climates as the predictor variables in the RF model. We then used the RF model, described above, to predict and map PVT class distributions (i.e., habitat types in Table 1) for each of the three GCM climate scenarios mentioned above. It is important to note that we were not predicting migrations of PVTs themselves under future climates; rather, we were predicting differences in spatial patterning of the climatic conditions where current PVT species assemblages may exist under future climates. A second caveat is that we did not allow for PVTs that were currently found outside the study area to migrate into the SWCC under future climates.

2.4. Mapping species distributions

We predicted current and future distributions of plant species by linking the PVT classes in Table 1 with the summarized field data collected from the habitat type classification development effort. In the Pfister et al. (1977) publication, Appendix C reports constancy (percent of plots in which a species occurred) and average cover (vertically projected average percent cover) for all sampled plant species that were used to develop each habitat type classification. We extracted constancy and cover information by PVT (Table 1) and then linked it to the habitat types (Table 1) in the PVT map. Although field data sampled by Pfister et al. (1977) were rich in many abundance measures, which we could easily have mapped, we mapped only species presence to match the resolution and form of other SDM map products used in our comparison (see next section). We defined a species as present when it occurred above 1% cover and was present on at least 50% of the plots sampled by Pfister et al. (1977).

We selected ten of over 70 possible species in the Pfister et al. (1977) constancy-cover tables to illustrate our method. These species were selected based on their importance in land management, and if they were mapped by other SDM mapping efforts. The tree species meeting our criteria were *Pseudostuga menziesii* (PSME), *Abies lasiocarpa* (ABLA), *Thuja plicata* (THPL), *Larix occidentalis* (LAOC), and *Pinus albicaulis* (PIAL). Undergrowth non-tree species were grouse whortleberry (*Vaccinium Hook. 1834;* VASC), beargrass (*Xerophyllum tenax* (Pursh) Nutt*;* XETE), twinflower (*Linnea borealis;* LIBO), queencup beadlily (*Clintonia uniflora* (Menzies ex Schult. & Schult. f.) Kunth; CLUN), and *Menziesia ferruginea* Craven; MEFE). We validated species maps by comparing our predictions to species presence as described in a FIA and ECODATA data sets that contained species cover estimates.

2.5. Comparison of BCMPVT and SDM products

We compared our spatial predictions of species presence with two existing SDM products developed by the U.S. Forest Service. The *FORECASTS* site (Forecasts of Climate-Associated Shifts in Tree Species) (https://www.geobabble.org/ForeCASTS/atlas.html), contains projections of North American tree species at 1 km resolution for the entire US under several climate scenarios (referred to as SDM-F). The Moscow Forestry Sciences Laboratory (SDM-M) created current and future tree atlases (0.0083 decimal degree resolution) with viability scores (0 to 1) for many trees of western North America (Crookston et al., 2010); http://charcoal.cnre.vt.edu/climate/species/index.php). Both of these efforts developed future species projections from climate derived from an earlier generations of global climate models (SRES, IPCC 2000). However, their scenarios assumed that current emission trends continue for the next several decades without modification (i.e. A1, A2). Therefore, we matched our RCP8.5 scenario with the A2 climate scenario used by these two products for the comparisons.

We used two methods to compare BCMPVT species maps with the two SDM map products (FORECASTS and Moscow FSL). We first compared the area occupied by each tree species in the SWCC across the three maps, and second, we used species presence from a set of plot data that was not included in the BCMPVT model-building to calculate a generalized accuracy (percentage of plots that each map correctly

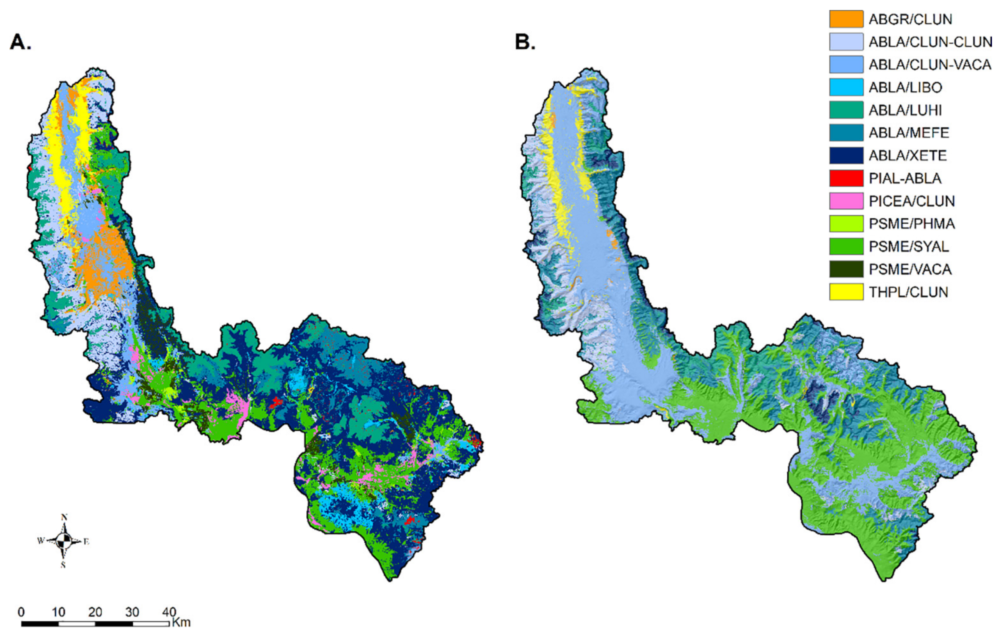

Fig. 2. Predicted Potential Vegetation Types (PVT; Pfister et al., 1977 habitat types) using the BCMPVT method for (A) current climate, and (B) future climate, based on the HadGEM2-ES GCM, RCP 8.5 high-emissions scenario. Definitions for the habitat types shown in the legend are in Table 1.

predicted tree species presence.

3. Results

3.1. PVT modeling and mapping

Most low elevation, valley bottom areas were mapped by the RF model using the current climate to the THPL/CLUN PVT in the northern parts of the SWCC (4% of SWCC landscape), ABGR/CLUN in the central SWCC (4%), and ABLA/CLUN (both phases) (18%) and PICEA/CLUN (3%) in the southern portion of the SWCC (Fig. 2; see Table 1 for acronym definitions). Mountain slopes were primarily mapped to the ABLA/XETE PVT on the south slopes (29%) and ABLA/MEFE on the north slopes (7%). Low elevation dry forests in the southern SWCC were dominated by PSME/SYAL (15%) and PSME/VACA on low elevation frost pockets (4%). High elevation forests were mostly ABLA/LUHI (11%) and PIAL-ABLA (< 1%).

The RF model performed reasonably well with an overall accuracy for the SWCC of 56% and kappa coefficient of 48%, which we determined to be quite good considering the large area (> 500 K ha), high number of PVTs (13), the inclusion of only climate variables, and the low number of plots (~2000) (Table 3) in the study area. The out of bag estimate of error rate of the model was 5% and the classification error among PVTs varied between 18% and 100%. As expected, PVTs with the highest accuracies were generally those with the highest number of plots (e.g., THPL/CLUN; Tables 1 and 3).

The spatial extent of PVTs changed dramatically in future climate (HadGEM2-ES GMC, RCP 8.5) as compared with current climate (Fig. 2, Table 3). The cool, mesic ABLA/CLUN-VACA habitat type increased in extent more than threefold, enveloping much of the northern SWCC valley bottoms (Fig. 2b), while cold, dry montane PVTs of ABLA/XETE and ABLA/LUHI decreased dramatically in extent (90% and 50%, respectively) from their current distributions (Fig. 2, Table 3). These PVTs appear to be replaced mainly by the warm, dry PSME/SYAL and the cool, moist ABLA/MEFE PVTs, both of which nearly doubled in extent (Table 3; Figs. 2 and 3). Differences in extent of future PVTs among the three GCMs (CanESM2, CNRM-CM5, and HadGEM2-ES, RCP8.5) were quite small for the SWCC (Table S.1, Fig. S.2).

Table 3
Modeled habitat type (Pfister 1977, Table 1) spatial distributions for current and future climate as a percent of the SWCC landscape. Classification errors (%) are in parentheses for the current distribution. User and producer accuracy (%) are shown for the PVT Random Forest model under current climate. For simplicity modeled future distributions for a single GCM (HadGEM2-ES RCP8.5) are presented here. See Table S.1 for PVT distributions for two other GCMs.

PVT acronym	Current distribution (%)	HadGEM2-ES RCP8.5 distribution (%)	User/producer accuracy (%)
ABGR/CLUN	4.35 (67)	0.33	36 / 53
ABLA/CLUN-CLUN	9.16 (32)	8.02	60 / 34
ABLA/CLUN-VACA	9.14 (44)	33.00	47 / 46
ABLA/LIBO	3.27 (69)	0	43 / 60
ABLA/LUHI	10.88 (48)	4.68	50 / 50
ABLA/MEFE	7.34 (84)	16.35	19 / 46
ABLA/XETE	29.07 (53)	2.85	47 / 61
PIAL-ABLA	0.63 (100)	0	50 / 25
PICEA/CLUN	2.74 (82)	0	8 / 29
PSME/PHMA	0.96(82)	0	33 / 50
PSME/SYAL	14.9 (38)	31.40	62 / 62
PSME/VACA	3.63 (97)	0	7 / 25
THPL/CLUN	3.92 (19)	3.39	86 / 79

3.2. Species distributions

We created species presence maps for five tree and five non-tree species for both current and future climate using the constancy-average cover information in Pfister et al. (1977) linked to mapped PVT classes (Fig. 4). Tree species that increased their distribution under future climates (HadGEM2-ES, RCP8.5) included PSME (89–95% areal extent of SWCC) and LAOC (36–45%), while ABLA (78–69%) and PIAL (12–5%) decreased under the HadGEM2-ES scenario (Table 4). Non-tree species with increased distributions in future climate included *Linnea borealis* (LIBO; from 33 to 45% areal extent of the study area), *Clintonia uniflora* (CLUN; from 29 to 45%), and *Menziesia ferruginea* (MEFE; from 11 to 16%). *Vaccinium scoparium* (VASC) and *Xerophyllum tenax* (XETE) decreased across the study region in future climate by 50% and about 10%, respectively (Table 4). Future, mapped distributions of tree and non-tree species for CanESM2 and CNRM-CM5 GCMs

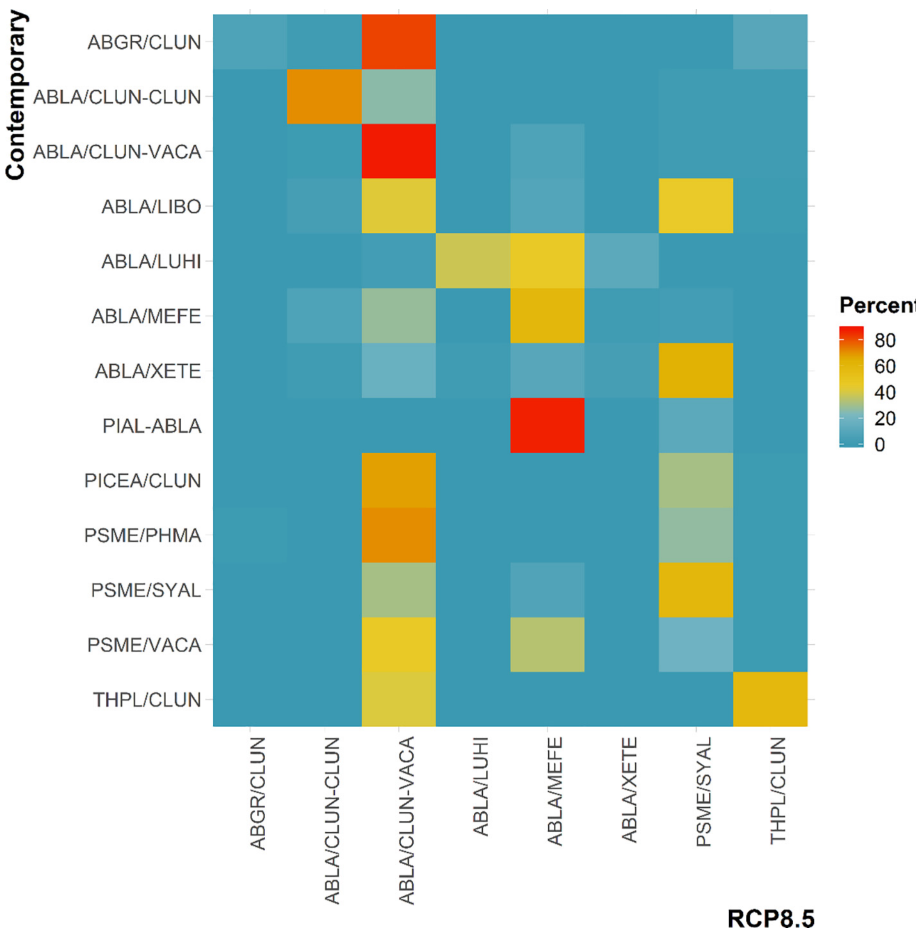

Fig. 3. Heat map derived from cross-tabulated matrix of the percent of each Potential Vegetation Type (PVT) predicted under contemporary (current) climate (horizontal axis) and future climate (HadGEM2-ES GCM, RCP 8.5 high-emissions scenario) (vertical axis). Note the large shift in ABLA and THPL PVTs to ABLA/CLUN-VACA and the shift from PIAL-ABLA to ABLA/MEFE. All habitat types (PVTs) are listed in Table 1.

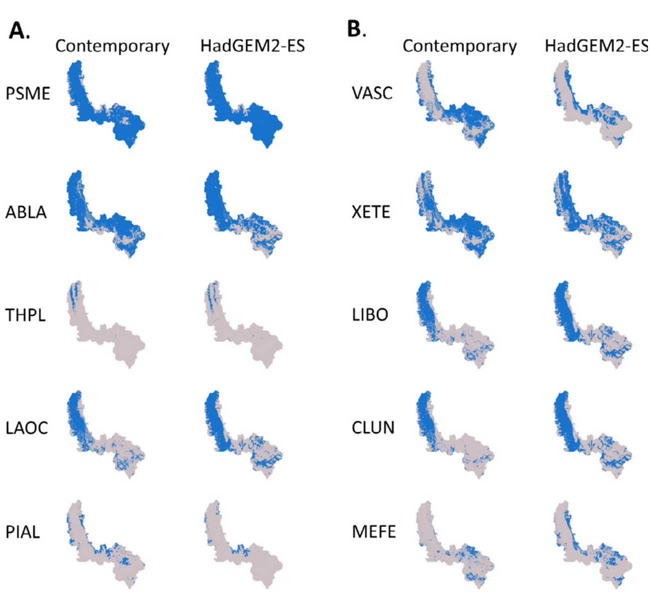

Fig. 4. BCMPVT predictions of (A) tree and (B) non-tree species distributions in the Southwest Crown of the Continent (SWCC) under current and future (HadGEM2-ES global climate model with the RCP 8.5 radiative forcing scenario) climates. Species presences is in blue and gray is species absence. A) Tree species include *Pseudotsuga menziesii* (PSME), *Abies lasiocarpa* (ABLA), *Thuja plicata* (THPL), *Larix occidentalis* (LAOC), and *Pinus albicaulis* (PIAL). B) Non tree species are *Vaccinium scoparium* (VASC), *Xerophyllum tenax* (XETE), *Linnea borealis* (LIBO), *Clintonia uniflora* (CLUN), and *Menziesia ferruginea* (MEFE). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Percent area occupied by five tree and five non-tree species as mapped using the BCMPVT approach, and for tree species predicted by FORCASTS (SDM-F) and Moscow FSL (SDM-M) SDM products for the current and future in the SWCC. Accuracies (% correctly predicted) for current tree distributions are in parentheses The BCMPVT future scenario incorporated climate projections from the HadGEM2-ES GCM, RCP8.5; SDM-F used the Hadley GCM, A1FI emissions scenario; SDM-M used the HADCM3 GCM, A2 emissions scenario. An NA value indicates that species maps were not available. Species names and acronyms are *Pseudotsuga menziesii* (PSME), *Abies lasiocarpa* (ABLA), *Thuja plicata* (THPL), *Larix occidentalis* (LAOC), and *Pinus albicaulis* (PIAL). Non tree species are *Vaccinium scoparium* (VASC), *Xerophyllum tenax* (XETE), *Linnea borealis* (LIBO), *Clintonia uniflora* (CLUN), and *Menziesia ferruginea* (MEFE).

Tree species acronym	Current			Future RCP8.5 or A2		
	BCMPVT	SDM-F	SDM-M	BCMPVT	SDM-F	SDM-M
	Tree species					
PSME	88.5 (77)	98.3 (77)	80.6 (72)	95.3	76.8	12.9
ABLA	77.8 (70)	87.7 (72)	81.2 (74)	68.6	7.4	5.1
THPL	3.9 (9)	0.0 (0)	5.65 (9)	3.4	0	13.7
LAOC	36.2 (44)	55.7 (42)	42.3 (54)	44.7	6.3	0
PIAL	11.5 (20)	58.8 (20)	39.7 (31)	4.7	3.1	0
	Non-tree species					
VASC	47.9	NA	NA	23.9	NA	NA
XETE	64.1	NA	NA	57.2	NA	NA
LIBO	32.6	NA	NA	44.7	NA	NA
CLUN	29.3	NA	NA	44.7	NA	NA
MEFE	10.6	NA	NA	16.4	NA	NA

were remarkably similar to the HadGEM2-ES-based predictions (Table S.2, Figs. S.3 and S.4). As a demonstration, we also created current and future maps of species abundance (canopy cover; %) (Fig. S.4). Here we found that both PSME and VASC abundance goes from 10% to over 50% canopy cover in the future in the southern portion of the SWCC, while THPL and LIBO increase by 20% in the future in the northern SWCC. Most species have little changes in canopy cover (PIAL, LAOC, CLUN, MEFE).

Accuracies for current climate tree species predictions were mixed: predicted distributions of the widespread species PSME and ABLA had greater than 70% accuracy, but prediction accuracy for localized species THPL, LAOC, and PIAL were substantially lower (9%, 44%, and 20%, respectively, Table 4), likely because of the smaller number of plots in PVTs where these species occur. No prediction accuracies were computed for the non-tree species, as our validation plots did not include undergrowth species abundance measures.

Again, future projections of the ten species for the other two GCM scenarios (CanESM2, CNRM-CM5) (Table S.2) were remarkably similar for both the tree species and non-tree species (Fig. S.3).

3.3. Comparison of BCMPVT and SDM products

Under current climate, predicted tree species distributions from the BCMPVT method were usually smaller in areal extent as compared with SDM maps, but within 10–30% for four of the five mapped tree species (Table 4). For PIAL, BCMPVT predicted its distribution across 12% of the study area versus the much larger extent mapped with SDM-F and SDM-M products (58% or 40% of the SWCC study area, respectively). A similar pattern is found with LAOC (SDM-F = 56%, SDM-M = 42%, BCMPVT = 36%) (Fig. 5).

For future climate (HadGEM2-ES GMC, RCP8.5), SDM-F and SDM-M mapped reduced cover area of −20 to −80% as compared with current climate distributions for four of the five mapped tree species. Distributional extents of ABLA, LAOC, and PIAL were very low (< 10% of the study area) in comparison with higher proportional distributions in current climate (Table 4). The BCMPVT method mainly predicted increased tree species distribution in future climate relative to current climate—for example, for LAOC (increase from 36 to 45%) (Fig. 5) and PSME (increase from 86 to 95%) (Table 4). Two tree species—THPL and PIAL—were absent from distributions predicted by SDM-F or SDM-M, but present in BCMPVT maps. Again, predicted BCMPVT tree species distributions were similar across the three GCMs (Table S2; Fig. S.3).

The BCMPVT method predicted species presence with equivalent and sometimes better accuracy as compared with SDM-F and SDM-M (Table 4). The SDM-F product had the highest accuracies for current distributions of PSME (77%), ABLA (88%), and LAOC (42%), but the BCMPVT product had comparable accuracies for these same species (77%, 70%, and 44%, respectively). The SCM-M product had similar accuracies as BCMPVT across most species but performed better for LAOC (54% vs 44%) and PIAL (31% vs 20%). Prediction accuracy for THPL was low (below 10%), for all approaches, likely related to plot representation.

4. Discussion

4.1. PVT models and map products

The BCMPVT method provided a finer scale, more flexible, and sometimes, more accurate alternative to SDM for mapping current and future vegetation. In contrast to SDM, the BCMPVT method can be used to map distributions and abundance plant communities, as well as individual tree species and rare or locally occurring plants. Resulting maps can provide valuable information on climate change impacts to ecosystems (e.g., represented by plant communities), ecological processes (e.g., fire regimes) and environmental characteristics (e.g., species abundance), particularly at the stand and landscape scales relevant for planning and implementing management activities. This study demonstrates that detailed PVT maps can be developed efficiently over large areas and at fine resolution, using advanced bioclimatic statistical modeling in a machine learning framework (Fig. 2). Although accuracies of mapped PVTs in this study were somewhat low for some PVTs (< 60%; Table 3), accuracies can be improved by increasing the number of field data plots, combining habitat types within a series, or including additional independent variables as predictors. We deliberately used only climate-derived variables in our effort to keep it simple, but other variables can easily be added to improve mapping accuracy. We created individual species distribution maps (Figs. 5, S.2–S.4) relatively easily by linking mapped PVT classes to the field sampled data for both current and future climates. This method could be extended to develop maps for any other ecological attributes that are summarized by PVT, such as wildlife habitat (Keane et al., 2003). Finally, this method could be used to develop future PVT maps for other BCM-derived PVTs via reanalysis. For example, projected future climate scenarios could be incorporated into the LANDFIRE Biophysical Settings product (Rollins et al., 2006, Rollins, 2009), a 30 m resolution, seamless data layer over the contiguous United States and Alaska, to provide a national map of future PVTs.

There are several advantages of the BCMPVT approach for climate change analyses in land management. As mentioned, PVTs are highly correlated with many ecological variables of great management concern, such as fire regimes (Barrett, 1988), site productivity (Pfister et al., 1977), and wildlife habitat (Marzluff et al., 2002). Predicted future PVT maps can be used to evaluate potential trends in fire, insects, disease, and a host of other issues (Arno, 1981, Crane, 1982). Moreover, because many plant species are represented in the constancy-cover tables associated with each PVT class, the BCMPVT map product can be used to estimate future ranges, and associated abundances (e.g., canopy cover), of numerous species and communities (Fig. S.4), especially those that are rare or have limited occurrence data to create a SDM map. This is important because our methods can be repeated, with minimal effort, as new climate scenarios are created or as additional species require mapping, while SDM products necessitate an entirely

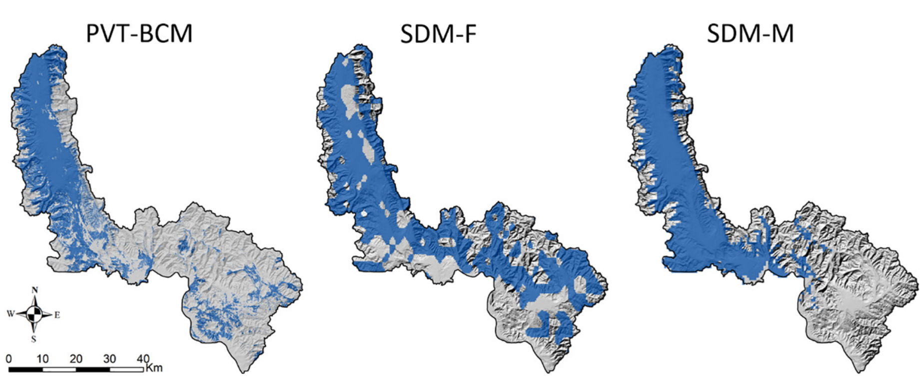

Fig. 5. Predictions of *Larix occidentalis* (LAOC) distributions using the BCMPVT model (HadGEM2-ES GCM, RCP 8.5 high-emissions scenario) and from two SDM products (SDM-F = FORECASTS, SDM-M = Moscow FSL) under current climate. The blue color indicates presence of LAOC. See Table 4 for prediction accuracy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

new analysis for each additional species and each new climate scenario. And importantly, PVTs provide a biophysical context for predicting future successional development (Arno et al., 1985, Steele and Geier-Hayers, 1989) and unique state-and-transition pathway models which have been built for each PVT (Keane, 2001, Keane et al., 2009). This allows the manager to also simulate landscape dynamics under active management scenarios in the future with the BCM-created PVT maps (Keane et al., 2008). This capability is of huge benefit, as predicting what will happen as a consequence of management actions, or lack of action, is a fundamental requirement of the land management planning process (Kimmins and Sollins, 1989, Boyce and McNab, 1994, Bellamy et al., 2001). Keane et al. (2009), for example, simulated both historical and future ranges and variation of vegetation composition and structure using a variation of our BCMPVT methods linked to a state-and-transition landscape dynamics model.

4.2. Predicted climate-driven ecological shifts

A careful examination of our modeled future PVTs and maps of tree species distributions provides insight into changing landscapes in the SWCC. As modeled with the HadGEM2-ES RCP 8.5 high-emissions climate scenario, the SWCC will lose (< 1% areal extent) six minor PVTs (ABGR/CLUN, ABLA/LIBO, PIAL-ABLA, PICEA/CLUN, PSME/PHMA, and PSME/VACA). The remaining three PVTs (ABLA/CLUN-VACA, ABLA/MEFE, and PSME/SYAL) will comprise over 80% of the future landscape. Overall, this will result in a decline in vascular plant species diversity, based on the species represented in the Pfister et al. (1977) cover data, and a shift from a diversity of mesic PVTs to the dominance of a warmer, drier PVT (PSME/SYAL). This homogenization of PVTs in the SWCC, and especially the predominance of PSME/SYAL, may also result in reduced potential for timber production (see Appendix C in Pfister et al. (1977)), increased fire occurrence (Barrett, 1988), and increased insect and disease-caused mortality (Loehman et al., 2018).

There are also major ecological consequences of the predicted shifts in the distributions of the ten species evaluated. The loss of whitebark pine (PIAL), a keystone tree species throughout the SWCC (Tomback et al., 2001) that is already in decline due to the exotic disease blister rust (*Cronatium ribicola*) (Keane et al., 1994), poses a great threat to ecosystem integrity across taxa because its large seeds provide critical food for many bird and mammal species (Hutchins, 1994). Loss of habitat for western larch (LAOC) is significant because it is one of the few conifers in the SWCC that can survive wildfire, projected to increase in the future warmer and drier climates (Riley and Loehman, 2016), and is integral to maintaining landscape resilience (Keane et al., 2018b). Predicted losses of subalpine fir (ABLA) and grouse whortleberry (VASC) from the SWCC have negative consequences for some rare wildlife species: ABLA is a major habitat component for the threatened Canadian lynx (*Lynx canadensis*), (Gonzalez et al., 2007), and VASC berries are an important food source for grizzly bears (*Ursus arctos horribilis*) (Kendall, 1986).

4.3. Limitations and uncertainties

The biggest challenge of this study was reconciling the spatio-temporal scales of the analysis with those of climate change. Although we used only data collected from within the SWCC study area, we acknowledge that future climates may create novel biophysical settings that could be best represented by PVTs that are outside of today's SWCC landscape, especially in warmer, drier lower elevations. For example, there were no dry, hot *Pinus ponderosa* (PIPO) habitat types in the SWCC plot data (although ponderosa pines are present in the SWCC), but it is entirely possible that some locations currently occupied by PSME PVTs may become so arid in the future that only PIPO habitat types can be sustained there. We attempted to rectify this by expanding our field data search area to a 100 km buffer around the SWCC to include these outlying habitat types, but this also increased the size of the area (5X), the number of mapped PVTs (from 13 to over 30 habitat types), the computing time required to simulate climate and ecosystem variables with WXFIRE (5X), and the number of included plots (from 2000 to 5000). These challenges made modeling and validation problematic and as a result we used only data from within the SWCC study area to illustrate our methodology.

The temporal scales of our input data were also incongruent with ecological scales of climate change. Our model used about 40 years of daily weather from the DAYMET database, which is only partially representative of the hundreds or thousands of weather years under which native vegetation has developed (Thornton et al., 2012). In addition, this small time-slice does not fully capture the cyclic nature of regional climate, caused by teleconnections such as the El Niño-Southern Oscillation and Pacific Decadal Oscillation (Gershunov and Barnett, 1998, Duffy et al., 2005). Future climate in our PVTs spanned a small 100-year time period, relatively short as compared with the developmental timeframes of a PVT, which could be millennia. It would take more than 100 years, for example, for some indicator plants to migrate to the newly created environs (Neilson et al., 2005), and conversely, it may take more than a century for some indicators to become absent from a site, especially the long-lived tree species (Aitken et al., 2008). Further, the projected, high seasonal and interannual variability of climate over the next 100 years may influence ecotonal shifts in PVTs (Levesque et al., 2019).

Another key uncertainty in PVT classification is the assumption that "climax" conditions, the key developmental stage in PVT classifications, are in equilibrium with climate (Daubenmire, 1966). As noted, warming climates are highly dynamic with directional trends over long time periods (Levesque et al., 2019). Areas in which climate drives a shift in PVTs (e.g. from cool, wet habitat type towards a warmer, drier type) demonstrate the potential for such climax conditions to shift over long time scales (e.g., hundreds of years) – which may not be evident over shorter periods (e.g., 25–50 years). Moreover, the species list (constancy-average cover tables) might be somewhat different for early seral conditions as compared to the late seral to climax conditions sampled to develop the PVT classifications (Arno et al., 1986). Moreover, the species list may fluctuate over shifts in climates (Loidi and Fernández-González, 2012). This is further exacerbated by of the role of exotics. This may be rectified by adding or modifying species abundance in the tables using data from new sampling efforts, legacy plot data, and other seral classifications, such as Arno et al. (1986). Finally, most PVT classifications are designed for sub-regional application depending on the objective of development. Pfister et al. (1977), for example, confined sampling to only the state of Montana, USA. Therefore, the BCMPVT approach may be need to be modified to be used at coarse scales, such as regional or continental scales (Pfister and Arno, 1980).

5. Summary

Management of today's landscapes requires both a view to the past and a look toward the future. We have ample evidence that changes in climate—including natural climate variability, but more significantly anthropogenic climate changes driven by the burning of fossil fuels—inevitably change landscapes through altered disturbance and changed ecosystem dynamics. Managers' abilities to develop proactive strategies for maintaining or promoting desired conditions are constrained by lack of information about future ecological patterns and processes (Loehman et al., 2020). Rather than relying on single-species models that ignore community and disturbance dynamics, it may be more adventagous to predict future changes in the spatial distribution of biophysical conditions that define a given PVT. These mapped units can then be used to evaluate species abundance changes, and also to assess changes in fire regimes, wildlife habitat, timber production, and exotic encroachment. We have described a comprehensive method to map PVTs across a large region, and have demonstrated how it can be used to create other map products that predict ecosystem characteristics of management concern into the future. We found that it took less than four months to create the current and future PVT maps. Most managers already have the field data for georeferenced PVT locations, which was the most difficult and costly part of our study. Because of its flexibility, scalability, and ability to represent vegetation communities and community-dependent ecosystem characteristics, we feel that the BCMPVT method is robust to land management concerns and provides an suitable alternative to mapping future species distributions in a context germane to management.

CRediT authorship contribution statement

Robert E. Keane: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing - original draft, Writing - review & editing. **Lisa M. Holsinger:** Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - review & editing. **Rachel Loehman:** Investigation, Methodology, Resources, Software, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Don Long, U.S. Forest Service, for providing field data and Chris Stalling, U.S. Forest Service, and two unnamed reviewers for their editorial comments for review of the paper.

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foreco.2020.118498.

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