Projected changes in habitat suitability for tree species in western Oregon due to climate change

Report to Bureau of Land Management

In partial fulfillment of Cooperative Assistance Agreement # L10AC20425

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July 23, 2014

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Scope and Objectives of this Report

This report has been prepared for the Bureau of Land Management (BLM) to lay the groundwork for a planned growth-and-yield modeling study evaluating the potential impacts and associated uncertainty of projected climate changes on a variety of forest management outcomes on BLM lands in western Oregon. This upcoming study will be conducted using the Climate extension of the Forest Vegetation Simulator (Climate-FVS) model developed and maintained by the US Forest Service. Climate-FVS incorporates bioclimate envelop projections as inputs to drive tree- and stand-level growth and mortality. The process by which Climate-FVS incorporates these factors is described briefly at the end of this report. This report focuses on the input data for Climate-FVS rather than the growth-and-yield modeling outcomes that Climate-FVS generates. The results of Climate-FVS simulations are to be presented in a separate report.

This report is intended to offer a comparative assessment of bioclimate envelope projections that feed into the FVS modeling environment with other independent research studies. The goal of this comparison is to identify areas where independent research studies have come to similar conclusions or where disagreement remains regarding the expected changes in climatic suitability for tree species and forest types that will be simulated using Climate-FVS. The underlying assumption is that areas that show strong agreement across modeling studies indicate higher confidence in the climatic effects on trees and forests within the study area.

In general, this report provides a synthesis and analysis of climate and forestry research that has been previously peer-reviewed and published in scientific journals, although some datasets that have not yet been per reviewed have also been included. This report utilizes datasets and processes from other research teams that were generated at a broad regional scale, and presents and analyses these data within a subset of their original geographic range (i.e., western Oregon). The primary focus in our review is to identify areas of agreement and disagreement regarding bioclimate envelope projections; it is not intended to more thoroughly evaluate the underlying causes of projected bioclimate envelope shifts due to specific environmental factors such as amounts of timing of precipitation, changes in temperature, etc.

This report is structured to offer a brief overview of climate trends and projections in the Pacific Northwest, the relevance of these changes to forest ecosystems in the region, and then a more detailed discussion and evaluation of the methodologies and tradeoffs involved in developing and interpreting bioclimate envelope projections. We close with a brief description of how Climate-FVS incorporates these bioclimate envelopes into its simulations that will be presented in a separate report.

The bulk of the analysis in this report consists of detailed comparison and discussion of several bioclimate envelope studies that are already publicly available and cover the Western Oregon BLM lands. This report considers pre-existing geospatial datasets covering this area that have either been peer-reviewed in scientific publications (e.g., Coops, Waring & Schroeder 2009; Crookston *et al.* 2010; Coops & Waring 2011) or have been published with sufficient documentation of methods to enable meaningful comparison and discussion (e.g., Bachelet 2014). As a review of existing datasets, we do not conduct new modeling projections in this review. Further, additional modeling approaches including process-models, gap models, and other approaches to bioclimate envelope modeling are underway in several research projects, and we encourage the BLM to consider these and other lines of research to further evaluate the potential impacts of climate change on forest ecosystems as they become available. We do not thoroughly address all these different modeling approaches in this report.

Introduction

Climate trends and projections for the Pacific Northwest

By the end of the twentieth century, the climate across the Pacific Northwest (PNW) is on course to be substantially shifted from the conditions under which our region's forests and other ecosystems have developed. Dalton and Mote (2013 chap. 2) report the latest round of climate modeling as projecting an increase in annual average temperatures of 2.0-8.5°F by mid-century. This warming is consistently projected to be more intense in summers, which are also more commonly expected to become drier as precipitation is commonly modeled to shift earlier in the season. The climate models are unanimous in projection of increases in heat and precipitation extremes and decreases in cold extremes.

Relevance of climate change to PNW forest ecosystems

Climate exerts a strong influence over forest ecosystem processes. Climate change may directly affect physiological processes such as individual tree growth, forest productivity, and mortality; climate may also indirectly affect forests by altering disturbance regimes including fire, pests, and disease. These effects have been summarized in reviews covering Washington state by Littell et al. (2010) and Oregon by Shafer et al. (2010).

Although gradual changes in temperature and precipitation will alter growing environments for many tree species and correspond to changes in growth and mortality, the effects of a changing climate on disturbances are anticipated to be much stronger drivers of forest ecosystem change:

> *The most rapidly visible and short-term effects on forest ecosystems will be caused by altered disturbance regimes, often occurring with increased frequency and severity. Interacting disturbances will have the biggest effects on ecosystem responses, simultaneously altering species composition, structure, and function.*
>
> *Vose et al.* (2012)

There are indications that ongoing changes in climate have already produced increased occurrence of drought and heat stress concurrent with a rise in reports in scientific journals of tree mortality in forests around the world (Allen *et al.* 2010). This global trend has been more strongly documented with observations in the western US, and directly linked to an observed increase in annual tree mortality (nearly doubled) across the region (van Mantgem *et al.* 2009).

The increased tree mortality rates documented by van Mantgem et al. (2009) were observed across the western US in every geographic region, elevation zone, genus, diameter class, and fire return interval considered, and supported with analysis indicating historical fire exclusion, structural changes and within-stand competition were not causing these changes; instead, increased temperature and water deficits were strongly correlated with mortality, leading the authors to conclude that "regional warming and consequent drought stress [are] the most likely drivers."

These early indicators of increased stress and mortality for trees and forests in the West are reinforced by remotely sensed disturbance detection which shows increased occurrence of disturbance within areas that have been identified through bioclimate envelope modeling as vulnerable to climate change (Waring, Coops & Running 2011).

The following analysis and review of projected climate change effects on the suitability of western Oregon lands is primarily focused on the potential climatic niches for individual tree species over the coming century. This review does not address the likely impacts of altered fire, pest, or disease dynamics, which are generally expected to exert an even stronger influence on PNW forests.

Climate Models and Emissions Scenarios

The recent surge in modeling studies of species responses to climate change have drawn from projections of climate variables produced in two waves of research that feed into the work of the Intergovernmental Panel on Climate Change (IPCC). In general, projections of future climate fundamentally involve two major components: General Circulation Models (GCMs) which simulate future climate based on a set of pre-defined drivers and climatic relationships and processes; and emissions scenarios describing the timing and amount of greenhouse gas emissions over the next century.

The principal data sources considered in this review were peer-reviewed based on their application of GCMs and emissions scenarios utilized in the Fourth Assessment Report of the IPCC. This collection of models and outputs is known as the third phase of the Coupled Model Intercomparison Project (CMIP3). Of the two available species-level bioclimate envelope data sources for western Oregon (described in greater detail below), the only GCM applied in both cases was the Canadian Centre for Climate Modeling and Analysis' CGCM3 model. Similarly, the emissions scenarios shared among these two data sources were limited to the A2 and B1 scenarios. More detailed descriptions of the A2, B1, and other emissions scenarios can be found in IPCC's Special Report on Emission Scenarios (2000).

Leading up to the Fifth Assessment Report of the IPCC, updated versions of GCMs have been developed, and emissions scenarios have been redefined primarily on the basis of the radiative forcing effect of GHG concentrations in the atmosphere (earlier emissions scenarios were defined based on socio-economic development trajectories). This new combination of models and emissions scenarios is referred to as the fifth phase of the Coupled Model Intercomparison Project (CMIP5). The new emissions scenarios applied by CMIP5 are referred to as Representative Concentration Pathways (RCPs), and identified by the radiative forcing value associated with a particular emissions schedule in terms of watts per square meter by 2100 (Vuuren *et al.* 2011). In this review, we will present data for future bioclimate envelopes based on four circulation models and two RCPs (4.5 and 8.5). These latest CMIP5 climate projections will also serve as the basis for the forthcoming growth-and-yield modeling study.

To make informed projections of species or ecosystem responses to climate change, projections by GCMs need to be scaled down to provide climate variables at a scale relevant for distinguishing species distributions or physiological processes. The down-sampling approaches used by the two groups of studies reviewed here are referenced in each of the respective bioclimate envelope publications (cited below).

Approaches to assess vulnerability of trees and forests to future climate change

In a review of approaches to estimate climate vulnerability, Rowland et al. (2011) offer two main types:

- Spatially-explicit models using correlative associations or environmental variables; and
- Evaluative frameworks that generate relative indices of climate change vulnerability.

This report focuses primarily on comparing two studies using different approaches to the application of spatially-explicit models. Both correlative statistical models and mechanistic process-based models rely upon several assumptions and have shortcomings. These are discussed in more detail further below. Evaluative frameworks can provide greater coverage of topics and factors not addressed through these spatially-explicit modeling approaches, and are a valuable and important resource for more comprehensive climate change vulnerability assessments and adaptation planning.

Evaluative frameworks relevant to the western Oregon study region considered in this report are available for comparison with projections of species distribution models. For example, Devine et al. (2012) provide an assessment of 57 tree species covering several sub-regions across Oregon and Washington using scores for five risk factors: distribution; reproductive capacity; habitat affinity; adaptive genetic variation; and major insect and disease threats. A similar spreadsheet tool designed for scientists in natural resource agencies which provides a Climate Change Vulnerability Index considering a species' exposure to climate changes (using down-scaled climate projections) and its sensitivity to those changes based on 20 different factors is also available (Young *et al.* 2011). It is worth noting that these evaluative frameworks can involve several subjective scoring and weighting systems, but we nevertheless encourage their consideration as one of many lines of evidence to support climate adaptation planning efforts.

In the eastern US, a hybrid approach combining both statistical models and modifying factors drawn from an evaluative framework approach has been developed (Matthews *et al.* 2011). The resulting projections for 134 different tree species, as well as several bird species, have been published online (USFS NRS Landscape Change Research Group 2014) and have been incorporated into several climate change adaptation and vulnerability assessments for six regional projects in midwestern and northeastern states (Northern Institute of Applied Climate Science 2015).

Spatially-explicit modeling applications

Although evaluative frameworks described above may offer a more comprehensive consideration of factors reasonably expected to affect a species' distribution under climate change, these frameworks are not inherently spatial in application, and do not directly address locations within a study area that are most vulnerable to climate change, an important consideration for prioritizing climate adaptation and mitigation efforts (Rowland *et al.* 2011).

There are two main modeling approaches used to inform our understanding of current and future species distributions in a spatially-explicit manner:

- Statistical models, also known as correlative, or empirical models
- Mechanistic models, also known as process-based models

Both of these approaches involve applying historically-observed relationships between species presence, abundance, or performance to identify the geographic areas (or ecological niches) that provide suitable conditions for a species to survive and grow.

A review of species distribution models by Guisan and Thuiller (2005) provides a helpful distinction between these two modeling approaches using the concept of the ecological niche:

- Process-based models apply physiological processes to simulate the ability of a species to survive given a set of abiotic/environmental variables. These models enable prediction of all the areas which provide conditions suitable for a species to occur, known as the species' *fundamental niche*.
- Empirical models use statistical approaches to identify predictive relationships based on the correlation of a species' presence/absence or abundance to observed climatic conditions and other environmental variables. As these models are based on the observed occurrence of a species, which is known to be constrained by a variety of factors such as competition, dispersal, etc., these models represent a subset of the *fundamental niche* referred to as the *realized niche*.

Generalized statistical and process-based models

Both of these types of models can also be applied at the species level or at the level of plant assemblages or biomes. There are several examples for the application of statistical niche-based models for predicting the suitable areas for biomes or plant assemblages (e.g., Hamann & Wang 2006; Rehfeldt *et al.* 2012; Wang *et al.* 2012). Similarly, process-based models applied to predict vegetation types or classes, known as dynamic global vegetation models are also available. The MC1 model is one such example for which future vegetation type projections under climate change have been published and are presented further below in this report (Bachelet *et al.* 2001).

Bioclimate envelope modeling applied to tree species in the Pacific Northwest

Several examples of species distribution and bioclimate envelope modeling have been published covering the Pacific Northwest. Hamann and Wang (2006) and Wang et al. (2012) utilize statistical models to predict future occurrence of vegetation types in British Columbia which are then used to infer the *realized niche* that would be available to individual tree species under future climates. The statistical approach of the Crookston et al. (2010) dataset, as well as the method used in this report for visualizing agreement or consensus in future climatic suitability projections are very similar to those of Wang et al. (2012).

The future climatic suitability projections of Crookston et al. (2010) and additional data published by the Moscow Forest Science Laboratory (http://forest.moscowfsl.wsu.edu/climate/) have been used for climate change adaptation planning including in northeastern Oregon (Blue Mountains Adaptation Partnership 2014). Another application of bioclimate envelope modeling using statistical models for management planning purposes can be found in several studies developing seed zones for Eastern white pine and Western larch in the US (Rehfeldt & Jaquish 2010; Joyce & Rehfeldt 2013) and for several species in British Columbia (Ying & Yanchuk 2006; Hamann, Gylander & Chen 2011).

McKenney et al. (2007, 2011) developed projections of future climatic suitability for 130 tree species under three circulation models and two emissions scenarios from CMIP3. These outputs from were prepared with a 10km x 10km grid cell resolution, and have been published online alongside numerous other species at http://planthardiness.gc.ca. Unfortunately, these data are not available in a downloadable format for analysis within a Geographic Information System (GIS). In addition, the 10x10km grid cell resolution significantly constrains the ability for interpreting climatic suitability for tree species at finer scales than multi-state or regional extents. Similarly, the statistics reported in these publications (as well as all the others reviewed) are generally reported as changes in the complete area of a particular species' bioclimate envelope size across an entire region or continent, and thus offer very limited inference at scales equivalent to BLM Districts or Resource Areas that occupy only a portion of the modeled range.

Two other recent modeling approaches (i.e., Coops *et al.* 2009, 2011; Crookston *et al.* 2010) have emerged with finer spatial resolution covering the PNW with substantial overlap in terms of individual tree species, circulation models, and emissions scenarios, enabling comparisons among these models. These approaches are investigated and presented in this report with a focus on the western Oregon BLM District extents, and described in greater detail in the description of methods used below. Recently published datasets with future projections of potential vegetation types for the western US using version 2 of the MC1 dynamic global vegetation model and CMIP5 climate projections are also discussed (Bachelet 2014).

A similar approach to statistically project climatic suitability for several tree species in the Pacific Northwest using CMIP3 climate projections and the MAXENT statistical program that were prepared by the GEOS Institute are available on the Databasin website (GEOS Institute 2013). However, these projections do not yet appear to have been subject to peer review, and several important methods for generating them (e.g., baseline climate period, training data, etc.) are not described at this website. These maps may offer an additional source to compare to future climate projections discussed in more detail in this report, but we have not incorporated these datasets formally into the statistical and graphical comparative analysis of bioclimate envelopes conducted here.

Assumptions, uncertainty, and tradeoffs in approaches to assess climate change impacts

The application of statistical and process-based models to project potential responses of species to climate change is continually evolving within the scientific community, largely owing to a variety of assumptions embedded within each of the distinct modeling approaches, and the importance of the variety assumptions and variables found to drive species performance under a changing climate (Franklin & Miller 2009; Wiens *et al.* 2009). As highlighted in a review by Pearson and Dawson (2003), despite the limitations imposed by the assumptions and uncertainty in species distribution models for future climatic suitability projections, these models remain "a useful first approximation as to the potentially dramatic impacts of climate change on biodiversity" so long as they are appropriately discussed with considerations of the uncertainty and geographic scale at which they may be applied.

Both statistical and process-based models rely upon a variety of assumptions, and are occasionally presented without indications of the uncertainty in the predictive abilities, and often without clear discussion of the appropriate scale for interpretation and application. Given the lack of data from the future which could serve to validate these models, the certainty of future bioclimate envelope projections using statistical models (as well as climate models themselves), including the appropriate geographic scale for interpretation is unquantifiable (Beale & Lennon 2012).

Statistical models rely upon assumptions that species distributions are primarily determined based on climatic variables (in contrast to factors such as competition with other species), that current species distributions used as training data are at equilibrium with climatic variables, and that species migration over time is not constrained by travel distances (Araújo & Peterson 2012). It is important to consider that these models generally rely upon an assumption that the relationship and interaction between biotic and abiotic variables are conserved into the future, but also that disturbances by humans and natural processes are also a common driver of current species distributions that may not be factored into the training data of species presence/absence used to build statistical relationships between climatic drivers and species habitat suitability.

The relative importance of climatic variables as primary drivers of species distributions has been challenged by Clark et al. (2011) based on research on 40 tree species in the southeastern United States. Clark et al. (2011) assert that competition and differential responses to climate over time by species in different life history stages appear to be stronger predictors of species distributions than the spatial correlation of species presence or abundance and climate variables. These findings highlight the importance of considering life history attributes when interpreting the outputs of species distribution models that do not account for these species qualities. Some mechanistic models, including gap models, are capable of incorporating the life history factors identified by Clark et al. (2011), but these have rarely been applied to projections of species suitability under climate change to date (Morin & Thuiller 2009).

One aspect of a species' life history that is often omitted in bioclimate envelope studies regards the consideration of a species' *regeneration niche*, which describes the conditions under which a species will naturally regenerate. An innovative study by Bell et al. (2014) used FIA plot data to evaluate climatic envelopes separately for seedlings and mature trees, and found significant divergence between the two. These authors further went on to conclude that climatic contractions can already be observed in the areas supporting the regeneration niche for six species considered. The contraction of the regeneration niche indicates that if/when mature trees die or are removed, these ecosystems are likely to see limited natural regeneration by those species. Although the regeneration niche is likely to play an important role in succession and natural regeneration of tree species in the future, it is worth noting that the datasets for bioclimate envelope projections reviewed in this report do not take this factor into account.

A separate important factor controlling the ability for trees and forests to adapt to changing climatic conditions lies in the genetics and phenotypic plasticity of localized variants of individual species. Most approaches to bioclimate envelope modeling, including those datasets reviewed in more detail in this report, tend to treat a species as genetically and phenotypically homogenous across its range. In reality, localized populations of trees are likely to exhibit varying degrees of adaptability that may or may not correspond to the full range of climatic conditions experienced throughout the species' entire range. In general, the limitation of bioclimate envelope projections to consider regions where a species variant is believed to occur constrains the range of climatic conditions for which that species will be predicted to suitable in the future. For example Wang et al. (2012) demonstrate a much stronger projection of climatic unsuitability for trees in British Columbia when individual seed zones, ecological provinces, or ecoregions are used as the extent of training data to build a bioclimate envelope projection as opposed to using climatic conditions across the entire species range in training data.

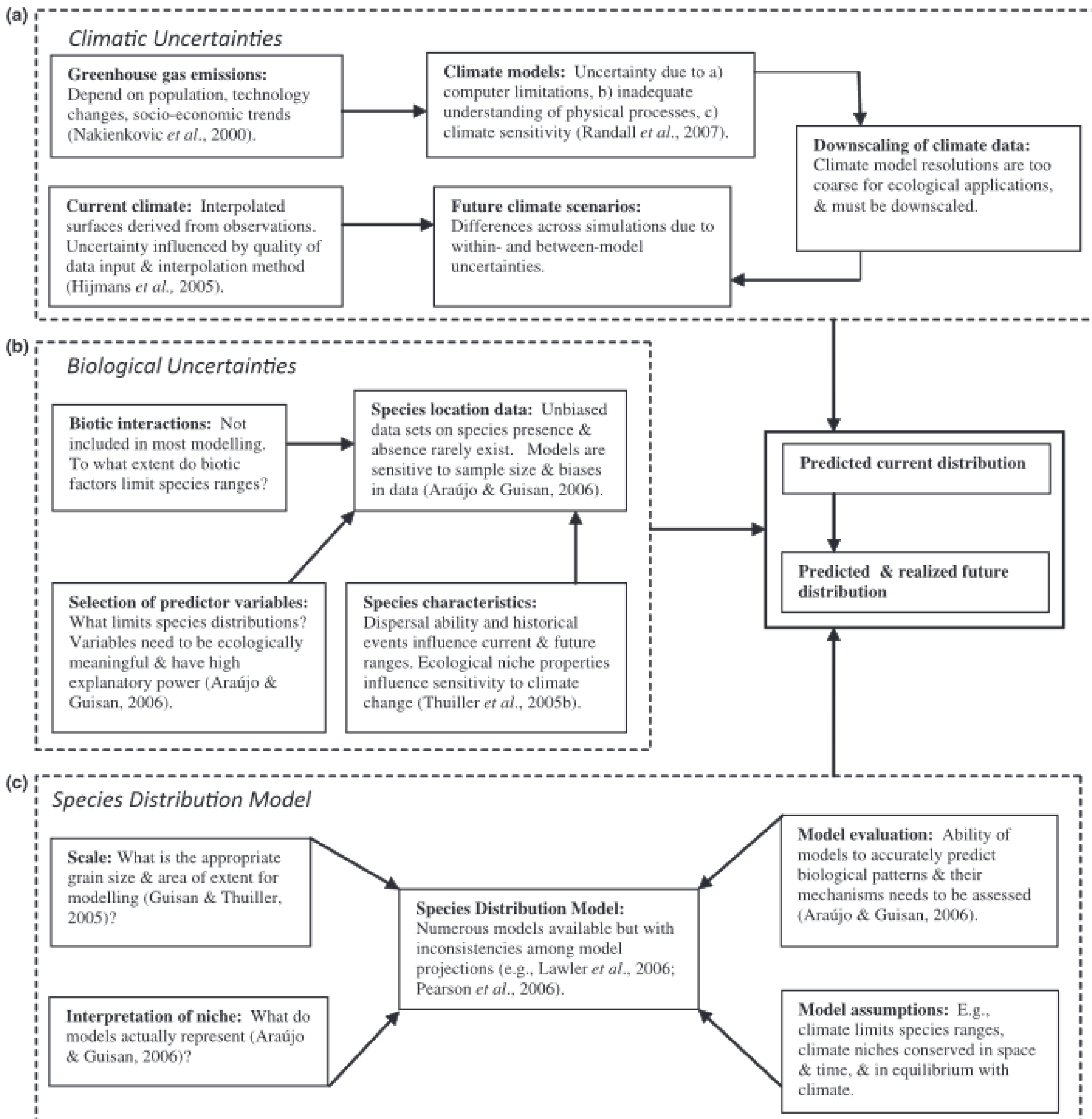
Bioclimate envelopes from statistical models relate the current or historical presence and/or absence of species or biomes to climatic variables. The forward-projection of these envelopes relies upon the assumption that current relationships derived by these models between climatic variables and species presence/absence are preserved over time, often ignoring changes in biotic interactions with abiotic factors such as CO_2 fertilization, altered pathogen or parasite conditions, and genetic evolution. In cases where novel combinations of climatic conditions occur in the future, statistical models are unable to offer an informed prediction of suitability, as they have only been trained on correlations of historical climate conditions with current species occurrence. Mechanistic models offer an important advantage to statistical models in this regard by being able to predict species responses to novel climatic conditions (Beale & Lennon 2012).

Although process-based models offer great promise for evaluating future climatic suitability, they require a detailed mechanistic knowledge of the physiological responses of individual species to a complex variety of abiotic drivers, as well as the underlying data for each of those relevant drivers across the study area (e.g., soil water holding capacity, the presence or scale of CO_2 fertilization by species, etc.), which are often unknown. This tradeoff in process-based models is believed to be the primary factor limiting their broader application to challenges like predicting species distributions under climate change (Jeltsch *et al.* 2008).

A major challenge in evaluating the performance of these models is that they are generally only available to be validated against observations of current species presence/absence or abundance, which represent the *realized niche* of a species (Beale & Lennon 2012). Process-based models, which predict the *fundamental niche* of a species, are thus generally expected to predict a greater suitable area for a species. This also corresponds to an increased likelihood that these process-based models would have greater error rates (i.e., errors of commission) in predicting current species presence in areas where a species could physiologically survive, but where other constraints such as competition with other species intervene (Cheaib *et al.* 2012). According to Beale and Lennon (2012): "methods that identify the fundamental niche in preference to the realized niche are preferable, despite the greater uncertainty associated with their predictions, because the narrower precision of the realized niche model probably underestimates uncertainty."

There are also a wide variety of sources of uncertainty that affect the confidence of bioclimate envelope models, and species distribution models more generally. Beaumont et al. (2008) provide a helpful visual overview covering the primary sources of uncertainty that feed into modeling future bioclimate envelopes, reproduced in Figure 1.

Figure 1: Major sources of uncertainty in bioclimate envelope modeling as described by Beaumont et al. (2008)



In general, there are three major groupings of sources of uncertainty identified by Beaumont et al. (2008): of future climate; of biological responses to climate and other environmental factors; and model parameterization and statistical uncertainty within the species distribution projections themselves.

Wiens et al. (2009) further describe the sources of model uncertainty including structural model uncertainty, the translation of niche associations into distributional probabilities by model algorithms, and the quantity and quality of training data including spatial and temporal extents, scales, and mismatches between datasets. Although model uncertainty within species distribution models is commonly reported, the uncertainty related to future climate projections and biological responses to climatic variables are rarely reported alongside them.

Reported divergence between process-based and statistical modeling outcomes

Several recent studies offer side-by-side comparisons of process-based and statistical models for future tree species projections under climate change. These studies consistently report that statistical models (and particularly the Random Forests model) are stronger than mechanistic models at predicting current species distributions based on correlated environmental variables, but that these statistical models also produce significantly larger predictions of shifts (and loss) of climatically-suitable ranges for most tree species than mechanistic models (Morin & Thuiller 2009; Keenan *et al.* 2011; Cheaib *et al.* 2012).

These results are intuitive based on the consideration of the types of ecological niches predicted by these models. Statistical models are unable to capture the phenotypic plasticity or local adaptation of tree species that may be captured in some mechanistic models (Morin & Thuiller 2009). Sensitivity analysis performed by Cheaib et al. (2012) and Keenan et al. (2011) both identified rising CO_2 concentrations (captured in some mechanistic models with physiological responses of increased nutrient and water use efficiencies) as a major factor affecting the greater predictions of productivity and survival in mechanistic models compared to statistical models; this effect was not shared across all species, particularly where species distributions are more strongly limited by hard climatic factors (such as freezing tolerance).

As mechanistic and correlative models are becoming more commonly applied and evaluated, recommendations for improving their accuracy and reliability are emerging, including the utilization of consensus-based or ensemble methods for correlative models (Prasad, Iverson & Liaw 2006; Marmion *et al.* 2009; Wang *et al.* 2012) along with emerging approaches to integrate mechanistic models or mechanistic features into correlative models or apply them both in an ensemble or consensus approach (Kearney & Porter 2009; Iverson *et al.* 2011). Both of these approaches have been repeatedly demonstrated to offer greater confidence in predicting current species distributions, and the strength of mechanistic models to more confidently project a species' *fundamental niche* under future climatic conditions is broadly recognized.

Bioclimate envelope projections used in this report

Before describing the specific methods applied by the datasets used in this study, it is important to clarify what these models are and are not projecting. Bioclimate envelopes are projections into the future of climatically-suitable habitat for a species. They are not direct projections of species distributions. The climatic suitability of a particular location may be expected to significantly affect the long-term productivity or survival of a species, but these factors interact with several other important drivers that are not captured in these models to determine whether or not a particular species actually occupies that niche in the future.

Statistical approaches like that of Crookston et al. (2010) are trained to recognize the combination of climatic variables that currently correlate strongly with species presence and absence, representing a species' *realized niche* or habitat. In contrast, mechanistic models, including the 3PG model which is applied in combination with a simple decision tree approach by Coops et al. (2009, 2011) and Coops and Waring (2011) utilize a handful of environmental drivers to simulate a species' physiological performance and identify the full geographic space capable of supporting the species, representing a species' *fundamental niche* or potential habitat. Neither of these approaches take into account the physiological response of trees to elevated CO_2 concentrations, competition between tree species, differential responses of a tree species based on its life history, or limits on the ability for a species to physically migrate to newly suitable niche space.

The Random Forests regression approach of Crookston et al. (2010)

Beginning with the development of a new spline model to down-scale climate projections using local weather stations (Rehfeldt 2006), a multiple regression approach called Random Forests has been applied to generate bioclimate envelope maps with 1km x 1km scale for biomes (Rehfeldt *et al.* 2006) and later for 75 tree species covering North America (Crookston *et al.* 2010).

Both the down-scaled climate projections as well as the species-specific bioclimate envelope data supporting these publications are publicly accessible and downloadable in GIS format from the Moscow Forestry Sciences Laboratory website (http://forest.moscowfsl.wsu.edu/climate).

In brief, the Random Forests regression approach utilized by Rehfeldt et al. (2006) and Crookston et al. (2010) generates thousands of regression models utilizing different subsets of training data (Forest Inventory & Analysis (FIA) plots with species presence/absence) and historical climatic variables (1961-1990 baseline). Each of these regression models are treated as 'votes', and the proportion of votes predicting a species' presence are interpreted as a "species viability score." More than 99.5% of all species observations within FIA plots for the species considered in this review occur in areas receiving a viability score above 0.5. Scores below 0.5 are interpreted within these publications (as well as within the Climate-FVS growth-and-yield model) as a combination of climatic variables that are not suitable for a particular species.

All maps of future projections of climatic suitability in this review (i.e., Map Sets 2-5) reflect a subset of the latest climate models and emissions scenarios from CMIP5. In contrast, the graphs and tables comparing species-level bioclimate envelopes are limited to the overlapping GCMs and emissions scenarios between Coops et al. (2009, 2011), Coops and Waring (2011), and Crookston et al. (2010), which are from CMIP3 (the CGCM3 growth model and emissions scenarios A2 and B1).

The future projections of bioclimate envelopes by Crookston et al. (2010) include three individual GCMs (CCSM4: The Community Earth System Model, GFDLCM3: Geophysical Fluid Dynamics Laboratory, and

HadGEM2ES: Met Office (UK)) as well as an Ensemble climate projection based on the combination of 17 different GCMs[1].

The hybrid process-model and decision-tree approach of Coops et al. (2011)

Statistical approaches such as the Random Forests regression modeling used in Crookston et al. (2010) lack the ability to incorporate direct physiological responses to environmental variables more commonly implemented in process-based models. The appeal of a process-modeling approach is attractive in light of expectations that higher ambient concentrations of CO_2, nitrogen deposition, and altered soil water availability may strongly influence physiological responses of plants to climate change. In addition, process-based models offer the potential to illuminate how novel combinations of environmental and climatic variables could affect productivity. This aspect of mechanistic models is a meaningful contrast to statistical models which build bioclimate envelopes based on the correlation of historically-observed climatic variables with species presence or absence. The reliability of applying statistical models to novel environmental and climatic conditions is unknown.

In an effort to incorporate the strengths of process-based models, which apply detailed physiological relationships relating a species' productivity under any environmental conditions, Coops et al. (2009) present a hybrid approach combining a generic process model parameterized for Douglas-fir with a simple decision-tree statistical model. In brief, Coops et al. (2009) utilize the 3PG process-model and simulate the productivity of Douglas-fir under historical climate conditions (1950-1976). The effects of several climate variables on Douglas-fir's growth are distilled into factors with wall-to-wall spatial coverage corresponding to what proportion of the maximum observed growth response for Douglas-fir occurs in any single grid cell given local environmental conditions. These factors incorporate the differential effects of four environmental variables (soil water availability, deviations from an optimum temperature, vapor pressure deficit, and frost frequency), scaled between 0 and 1 based on their impact on Douglas-fir productivity. These Douglas-fir-referenced factors are then used to build decision-trees for several other tree species using training data of presence/absence of these species from FIA plots.

This method has since been applied by Coops and Waring (2011) and Coops et al. (2011) to predict bioclimate envelopes for 15 coniferous tree species. It is important to note that at the time these research projects were ongoing, monthly climate projections were not incorporated to drive a process-modeling for future climate projections. That is, these studies do not apply process-modeling to future climate data; instead a single decision tree for each species derived from process-modeling of historical climate conditions is applied to future climate variables. These projections use CMIP3 data and include the A2 and B1 emissions scenarios with the CGCM3 circulation model, down-scaled to 1km x 1km resolution.

Although current climate suitability is presented in Coops et al. (2011) in terms of resilience or vulnerability to climate change using a threshold defined by the probability of occurrence from process-

[1] The 17 GCMs included in the Ensemble are: BCC-CSM1-1; CCSM4; CESM1-CAM5; CSIRO-Mk3-6-0; FIO-ESM; GFDL-CM3; GFDL-ESM2G; GFDL-ESM2M; GISS-E2-R; HadGEM2-AO; HadGEM2-ES; IPSL-CM5A-LR; MIROC5; MIROC-ESM-CHEM; MIROC-ESM; MRI-CGCM3; NorESM1-M. More information about the modeling approach of Crookston et al. (2010) is available online at http://forest.moscowfsl.wsu.edu/climate/future/details.php.

modeling with climatic data from 1976-2006, future projections of suitability in this dataset do not rely on a threshold process for declaring suitability or unsuitability. Instead, the annual average climatic values for 2020, 2050, and 2080 were plugged into a single decision tree for each species and given a binary suitable/unsuitable rating for each pixel (Coops and Waring, personal communication). Much of the data from these publications is publicly available for download in proprietary ArcGIS formats at http://databasin.org.

The MC2 dynamic global vegetation model approach of Bachelet (2014)

Data from the Dynamic Global Vegetation Model MC1, version 2 (also referred to as MC2) is also available with projections of potential vegetation types (as opposed to individual species) using a process-model approach. As described in Bachelet (2001), the MC1 model contains a biogeography module that predicts the composition of deciduous and evergreen trees, as well as C3 and C4 grasses and classifies these combinations into one of 21 different vegetation classes based on monthly temperature and precipitation variables. Although MC2 also contains modules to simulate biogeochemical cycling as well as wildfire, these modules are not described in detail in this report.

To generate future projections of potential vegetation types under climate change, Bachelet (2014) utilize climate data from 10 CMIP5 GCMs[2] and emissions scenarios RCP 4.5 and RCP 8.5 that were down-scaled using a process known as Multivariate Adaptive Constructed Analogs (Abatzoglou & Brown 2012). The MC2 model was run to generate projections of potential vegetation types with a resolution of 4km pixels.

Methods for comparing bioclimate envelopes and mapping consensus

To evaluate the level of agreement between these two data sources, maps and graphics were generated for at least six major tree species identified by BLM staff: Douglas-fir, Western hemlock, Western redcedar, Ponderosa pine, Grand fir, and Engelmann spruce. Where space allows, additional species have been added to tables and graphs for additional context. The maps presented in Map Set 1 show the predictions of suitability/vulnerability by Coops et al. (2011) based on baseline climate data from the 1976-2006 timeframe, while those from Crookston et al. (2010) are based on climate data from the 1961-1990 timeframe.

Geospatial and statistical analysis comparing these two datasets in tables and graphs was constrained to the geographic extent of western Oregon BLM District boundaries. Graphs and tables are utilized to describe the level of agreement between these data sets under the CGCM3 model and A2 and B1 emissions scenarios.

In this review, maps of future bioclimatic niches are limited to the latest CMIP5 climate projections derived using the same process described in Crookston et al. (2010) and downloaded from the Moscow Forestry Sciences Lab website.

[2] The 10 GCMs considered in this modeling study include: BCC-CSM, CCSM4, BNU-ESM, MIROC-ESM, CSIRO, GFDL-ESM2M, GFDL-ESM2G, MIROC-ESM-CHEM, CanESM2, and CNRM-CM5.

Statistical, graphical, and spatial assessments of model accuracy and agreement

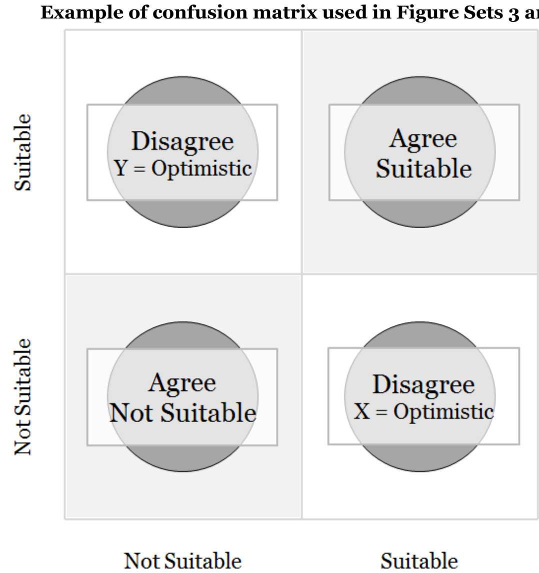
Metrics useful for assessing of the accuracy of these two models in terms of predicting current species presence and absence are presented in Table 1 and displayed in Figure Set 2. In particular, measures of prediction errors compared to actual presence absence for FIA plots within the western Oregon BLM District extent are shown along with the True Skill Statistic (Allouche, Tsoar & Kadmon 2006), which combines ratings of model performance on both errors of omission and commission.

To quantify the level of agreement between the Coops et al. (2011) current habitat suitability ratings and the Crookston et al. (2010) current species viability scores, the Concordance Correlation Coefficient developed by Lin (1989, 2000) is employed. In brief, this metric was originally developed to compare distinct scoring or rating systems for inter-compatibility and reproducibility, and describes the correlation of two variables to a 1:1 relationship.

To graphically display the agreement/disagreement between current and future ratings of bioclimate envelopes between Coops et al. (2011) and Crookston et al. (2010), Figure Sets 3 and 4 utilize a bubble graph layout similar to a 'confusion matrix'. These graphics display the acreage (in thousands of acres) as classified by each rating system shown along the x-axis and y-axis. The gray-shaded cells in these tables represent agreement between the two rating systems.

A preponderance of acreage in the lower right-hand cell indicates the rating system on the x-axis is more 'optimistic' in terms of species suitability than the rating system on the y-axis. Conversely, a preponderance of acreage in the upper left-hand cell indicates the rating system on the x-axis is more 'pessimistic' than the rating system along the y-axis. Graphs that show a preponderance of acreage within the lower left-hand and/or upper-right hand cells indicate strong agreement between the two models. In Figure Set 4, the rating system for Crookston et al. (2010) is converted to a binary rating, with values above/below a "species viability score" of 0.5 rated as suitable/unsuitable.

Example of confusion matrix used in Figure Sets 3 and 4



Maps covering the state of Oregon in Map Set 1 provide the location of FIA plots where each species was observed to be present or absent, overlaid with current habitat suitability as defined by each data source. It is worth noting the geographic locations of FIA plots are 'fuzzed' to protect the identity of landowners and the integrity of these plots. These 'fuzzed' locations are used for calculating model prediction accuracy for current presence/absence shown in Table 1 and displayed in Map Set 1.

Mapping consensus among future bioclimate envelope projections of Crookston (2010) and Bachelet (2014)

To map future bioclimate envelopes projected by Crookston et al. (2010), we show the level of agreement or consensus among several different GCMs similar to the approach of Wang et al. (2012), although we do not combine multiple RCPs/emissions scenarios in this study. Areas are mapped according to whether the results are shared across all GCMs (unanimous agreement), or whether one or more GCMs produce conflicting projections of climatic suitability. These are displayed in Map Set 2. Map Set 3 displays the projected expansion of several species that are predicted to see the largest growth in newly climatically-suitable habitat in western Oregon due to future climate change with a visualization of the level of agreement among GCMs.

Projections of specific potential vegetation types by the MC2 model under high and low emissions scenarios are provided in Map Set 4, where the most commonly chosen potential vegetation type predicted among 10 separate GCMs is displayed. In Map Set 5, the level of agreement/disagreement in these projections among 10 GCMs is visualized to identify areas where potential vegetation type changes (or retention) are commonly predicted across these GCMs.

Results

Comparing Coops and Crookston

Current habitat suitability, Coops v. Crookston

The level of agreement between Coops and Crookston, as indicated by the Concordance Correlation Coefficient based on ratings of current climatic suitability, showed relatively poor agreement for all species (see Table 1). The strongest concordance was observed for Douglas-fir, followed by Western hemlock and Western redcedar, and Ponderosa pine. Validation statistics we calculated using FIA presence/absence for each species within the extent of the western Oregon BLM District boundaries suggest that the Random Forests approach applied by Crookston et al. (2010) is generally more accurate both in terms of predicting presence as well as absence of most tree species. Specific exceptions include better performance by Coops et al. (2011) at predicting species presence for Douglas-fir and Western redcedar (particularly when based on 1976-2006 climate data), and predicting species absence for Engelmann spruce.

Crookston et al. (2010) showed better prediction performance for all species as measured by the True Skill Statistic (see Table 1 and Figure Set 2). For the most widespread species (e.g., Douglas-fir, Western hemlock, Western redcedar, and Ponderosa pine), Coops et al. (2011) showed lower specificity (less adept at predicting species absence) than Crookston et al. (2010); depending on whether the 1976-2006 or 1950-1976 climate data are used, Coops et al. (2011) showed comparable sensitivity (ability to predict species presence) to Crookston et al. (2010).

In general, the Random Forests approach applied by Crookston et al. (2010) appears to spatially over-fit climatic suitability to FIA plot locations used as training data. This is apparent in maps of current suitable ranges for Douglas-fir and Western redcedar that tightly fit observations in FIA plots, but which suggest that the climate within the Willamette Valley would be unsuitable for Douglas-fir and that many locations along the Coast Range in western Oregon would be unsuitable for Western redcedar. In contrast, the process-modeling approach of Coops et al. (2011) commonly predicts suitability in many locations where that species is not observed in FIA plots (see Map Set 1). The overlaid species distribution ranges of Little (1971) help provide a reference for more broadly defined zones believed to historically support these species.

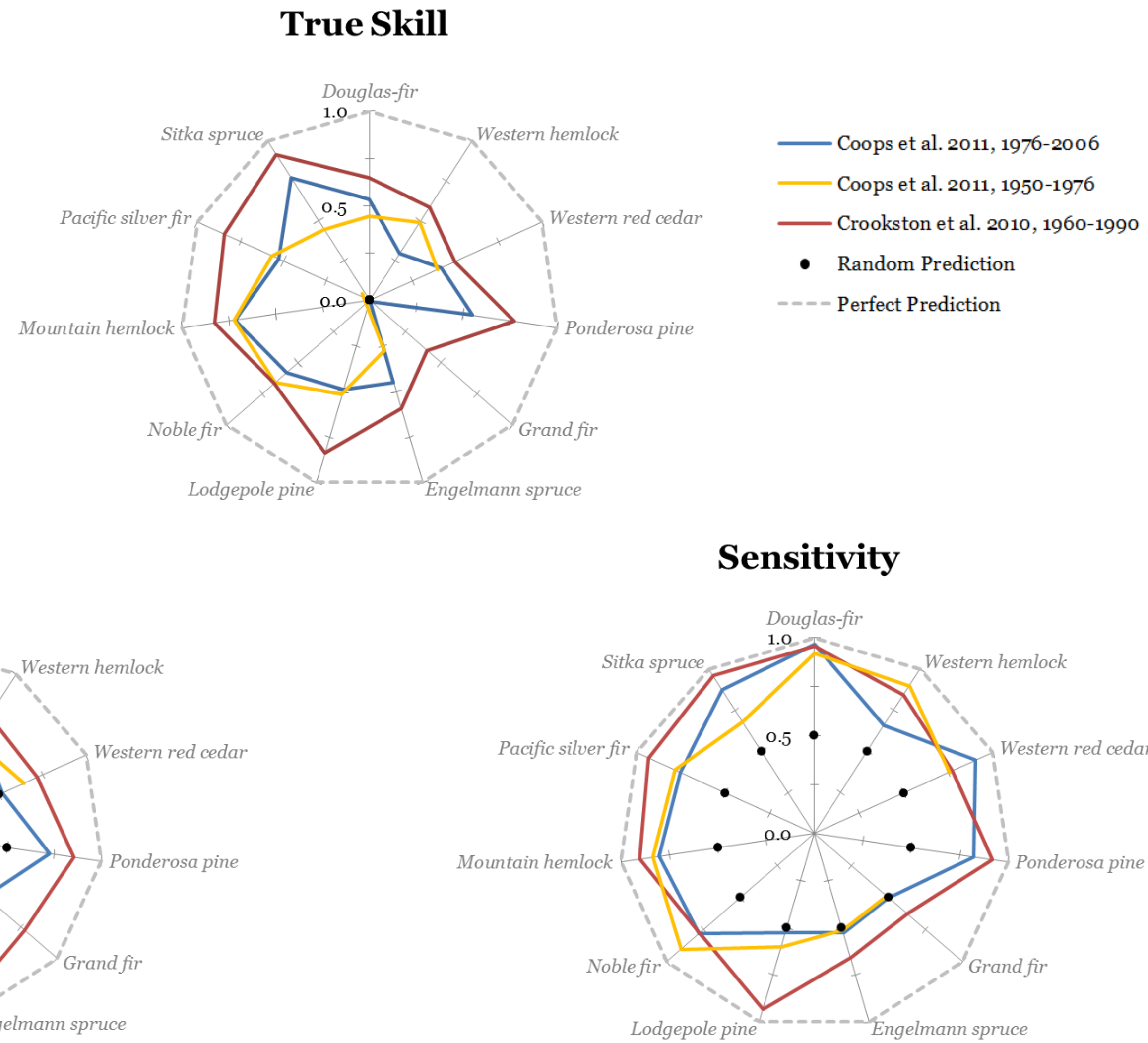
The current bioclimate envelope maps by Crookston et al. (2010) tightly fit the FIA plot data. The projections by Coops et al. (2011) are more prone to “false-positives” where the presence of a species is predicted by the model, but not observed in any nearby FIA plots. This is indicated statistically by the consistently larger commission error rates in Table 1 for most species under the model of Coops et al. (2011). This aspect can also be observed in Map Set 1. For example, Coops et al. (2011) bioclimate envelopes predict suitability for Douglas-fir in southern Oregon east of the Cascade Range, and for Western hemlock and Western redcedar along the SW Oregon coast, despite the general absence of these species from FIA plots in these areas.

Table 1. Current habitat suitability error rates and agreement within BLM District Extent: *Comparing Coops et al. 2011 and Crookston et al. 2010 predictions of presence/absence at FIA plot locations.*

Species	Commission Error (predict presence when absent)			Omission Error (predict absence when present)			True Skill Statistic[†]			Concordance Correlation Coefficient*
	Coops et al. 2011		*Crookston et al. 2010*	*Coops et al. 2011*		*Crookston et al. 2010*	*Coops et al. 2011*		*Crookston et al. 2010*	
	1976-2006	*1950-1976*	*1961-1990*	*1976-2006*	*1950-1976*	*1961-1990*	*1976-2006*	*1950-1976*	*1961-1990*	
Douglas-fir	77.1%	91.9%	44.1%	0.7%	0.7%	2.4%	0.53	0.44	0.65	0.88
Western hemlock	39.9%	66.5%	30.7%	31.1%	3.8%	12.8%	0.29	0.49	0.58	0.81
Western redcedar	93.7%	46.8%	31.7%	0.7%	17.0%	19.7%	0.42	0.40	0.49	0.81
Ponderosa pine	32.5%	--	16.2%	14.6%	--	7.5%	0.55	--	0.77	0.76
Grand fir	15.0%	20.8%	14.1%	84.7%	82.5%	51.3%	0.01	-0.05	0.40	0.13
Engelmann spruce	0.9%	1.7%	3.5%	88.9%	94.4%	50.0%	0.45	0.27	0.59	0.46
Noble fir	19.6%	29.4%	8.9%	22.5%	7.5%	26.3%	0.58	0.66	0.67	0.67
Pacific silver fir	22.0%	22.0%	9.5%	25.2%	21.1%	6.5%	0.53	0.57	0.84	0.53
Sitka spruce	10.6%	18.6%	5.0%	12.6%	38.7%	3.9%	0.77	0.45	0.91	0.75

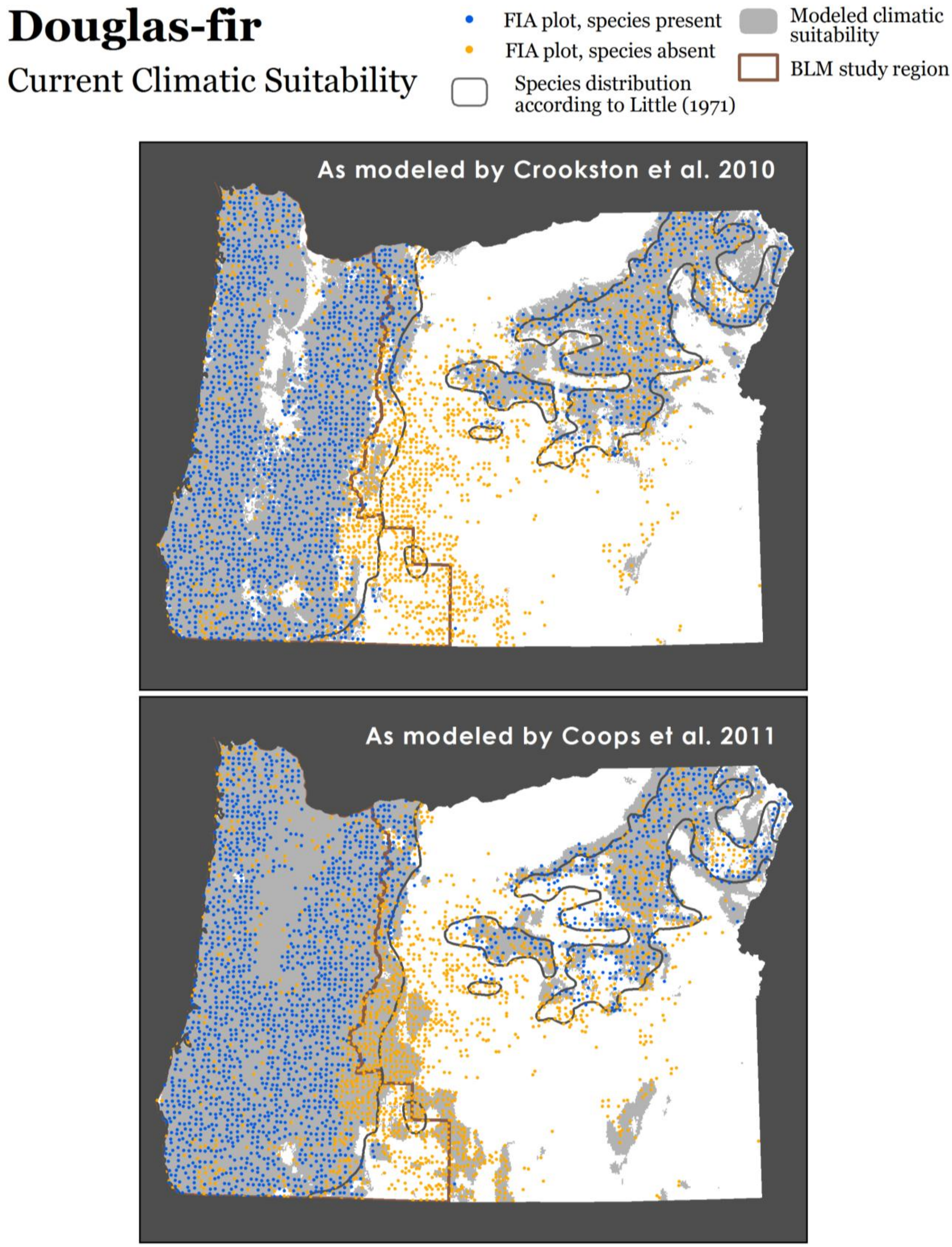
Notes: [†]*The True Skill Statistic combines the proportion of commission and omission errors to give a rating of model prediction accuracy that ranges between -1 and +1, with +1 corresponding to perfect prediction, 0 to random prediction, and -1 to completely inaccurate prediction; it is recommended by Allouche et al.* (2006) *for accuracy assessment in species distribution models.*
**The Concordance Correlation Coefficient, developed by Lin* (1989, 2000) *describes the level of agreement between two variables. The coefficient presented here compares the 1976-2006 timeline from Coops et al. (2011) with Crookston et al. (2010). McBride* (2005) *has recommended the following interpretation of the Concordance Correlation Coefficient in terms of the strength of agreement:*
>0.99 = almost perfect | 0.95-0.99 = substantial | 0.90-0.95 = moderate | <0.90 = poor

Figure Set 2: **Prediction accuracy of species presence/absence:**
comparing Coops et al. 2011 and Crookston et al. 2010



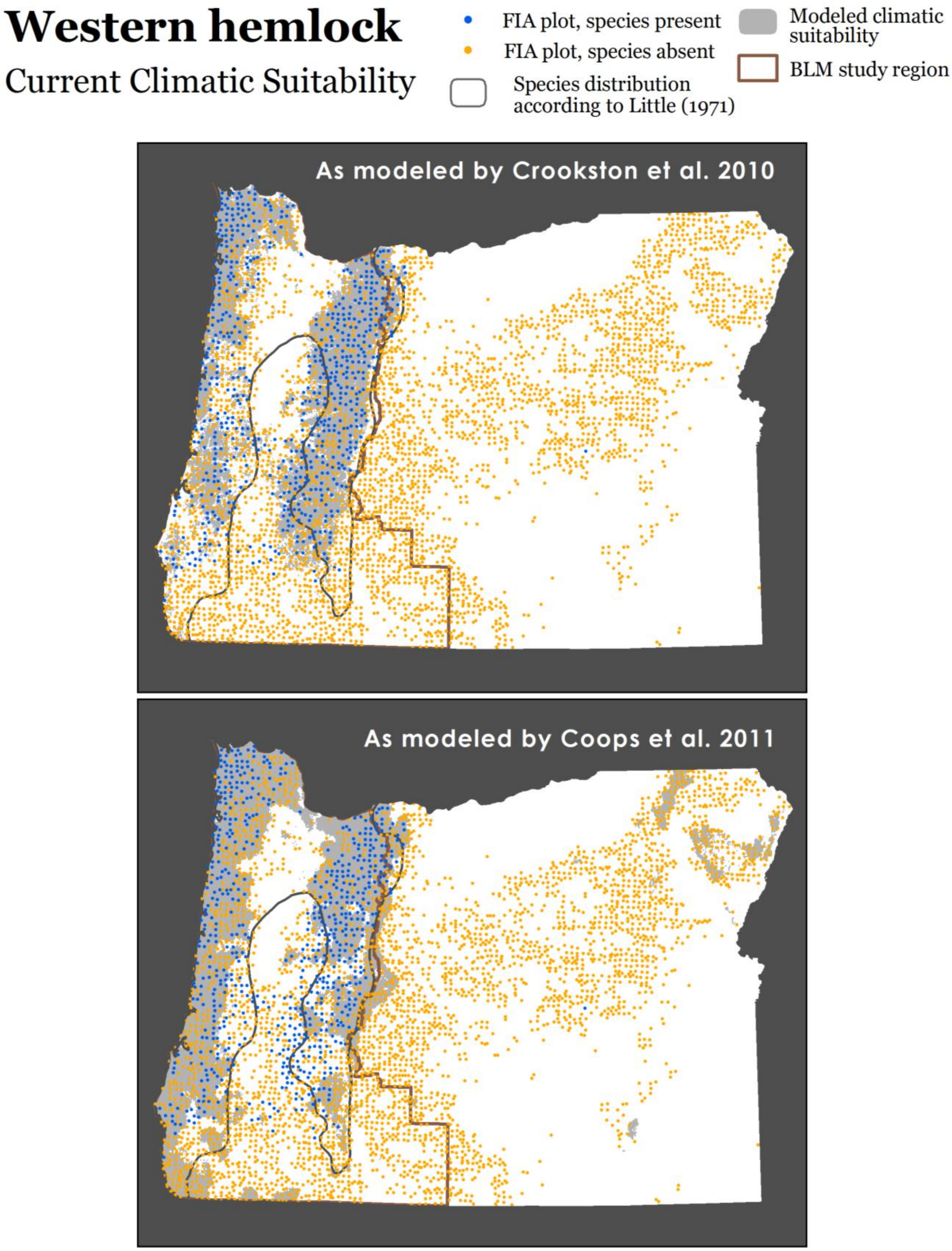
Note: The True Skill Statistic combines ratings of model Specificity and Sensitivity. As described by Allouche et al. (2006): "Sensitivity is the proportion of observed presences that are predicted as such, and therefore quantifies omission errors. Specificity is the proportion of observed absences that are predicted as such, and therefore quantifies commission errors."

Map Set 1: Fit of current bioclimate envelope models with inventory data



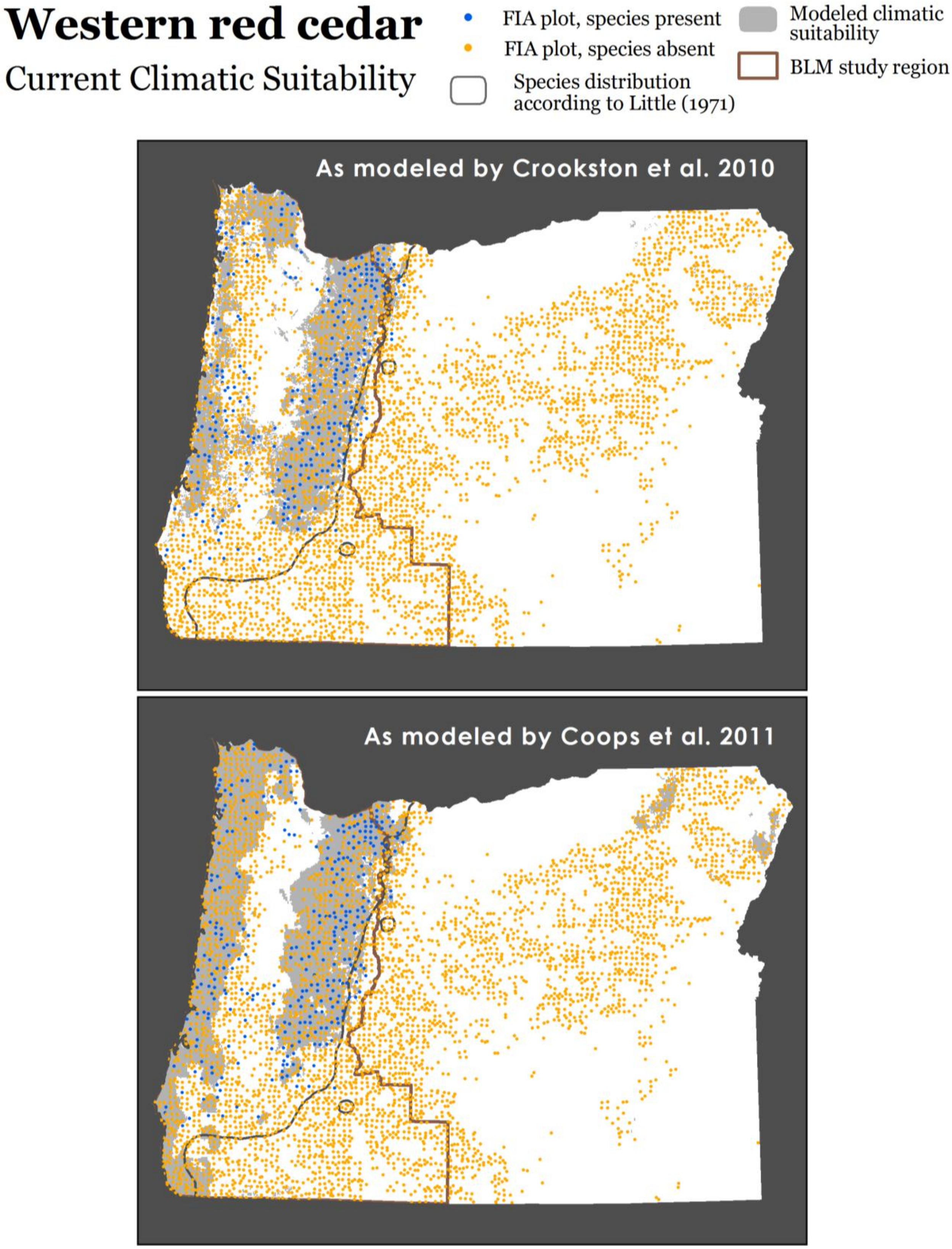
Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Map Set 1 (continued)



Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Map Set 1 (continued)



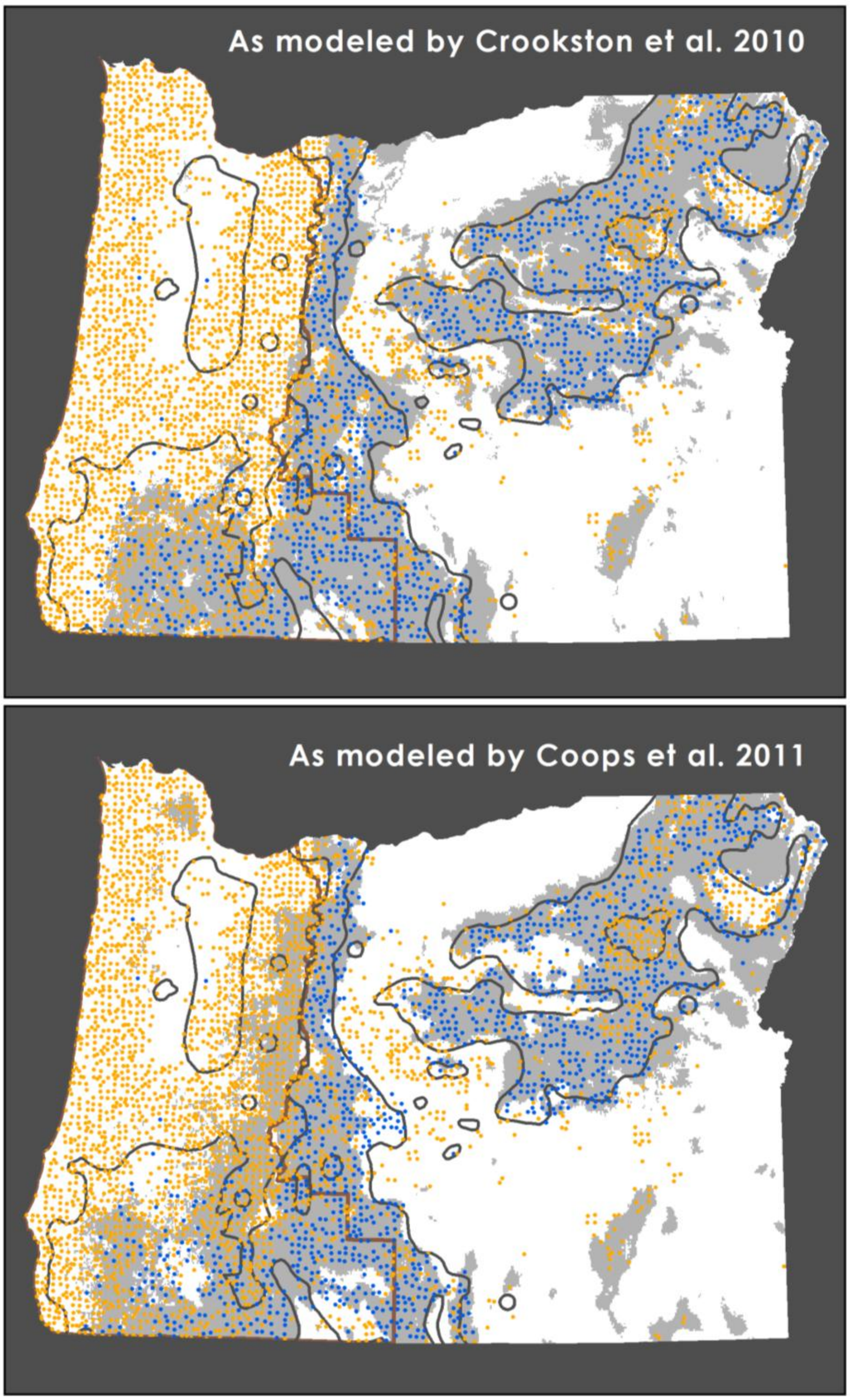
Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Map Set 1 (continued)

Ponderosa Pine

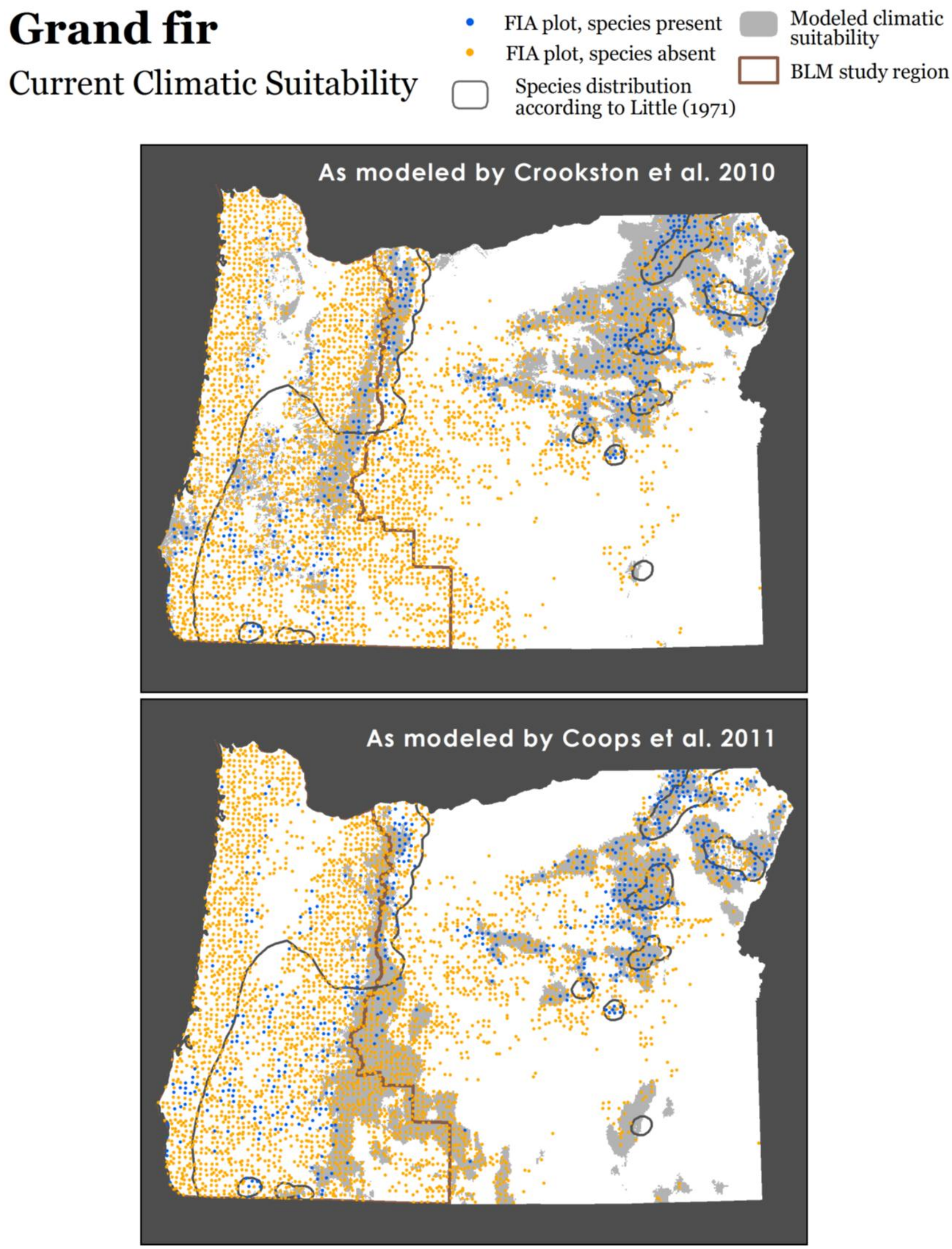
Current Climatic Suitability

- FIA plot, species present
- FIA plot, species absent
- Species distribution according to Little (1971)
- Modeled climatic suitability
- BLM study region



Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Map Set 1 (continued)



Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Map Set 1 (continued)

Note: These maps compare estimates of current climatic suitability based on statistical modeling using FIA plots as training data. Climatic suitability is not synonymous with species distributions. These maps offer a sense of how well the suitability rating of each study fits actual field observations of species presence and absence. For context, the species range distribution of Little (1971) is also overlaid.

Vulnerability and resilience in the Coops dataset

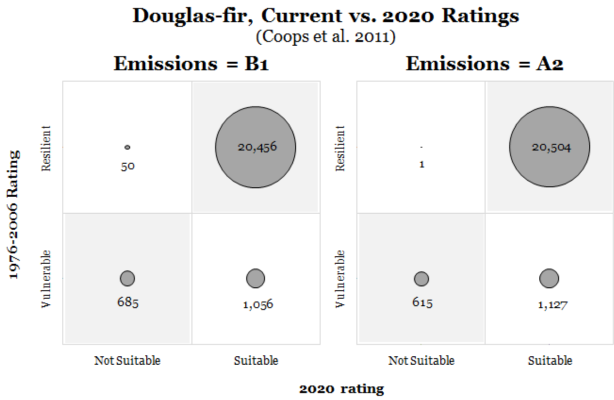
In Coops et al. (2011) and Coops and Waring (2011), the authors provide a rating system to indicate the locations that, as of 2006, are vulnerable or resilient to climate change for each species. The ratings used in this review are from Coops et al. (2011), which were derived based on the process-modeling for Douglas-fir and the application of Douglas-fir referenced decisions trees to predict presence/absence for other species from 1976-2006; those grid cells where the climate did not support the growth of the species in 50% of the years modeled were declared vulnerable to climate change.

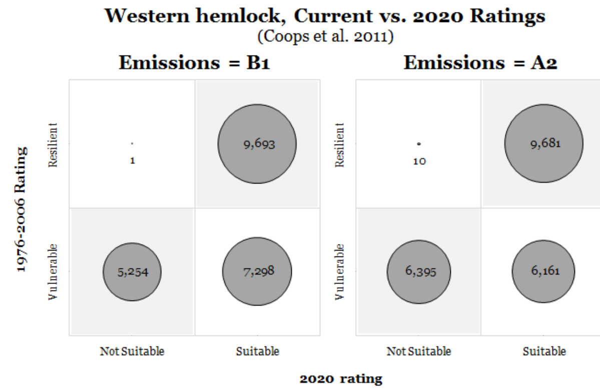
Although the distinction between this threshold-based rating for historical and current suitability with future projections was not apparent from the journal article itself, personal communication with both Nicholas Coops and Dick Waring helped elaborate the process described earlier for predicting habitat suitability under future climate scenarios. As described above, although current climate suitability is presented in Coops et al. (2011) in terms of resilience or vulnerability to climate change using a threshold defined by the probability of occurrence from process-modeling with climatic data from 1976-2006, future projections of suitability in this dataset do not rely on a threshold process for declaring suitability or unsuitability. Instead, the annual average climatic values for 2020, 2050, and 2080 were plugged into a single decision tree for each species and given a binary suitable/unsuitable rating for each pixel (Coops and Waring, personal communication). This difference in approach between current rating systems and future rating systems within this study suggest that the validation statistics presented in the original publication, as well as in this review, offer no meaningful inference with which to gauge the reliability of the future projections of bioclimate envelopes.

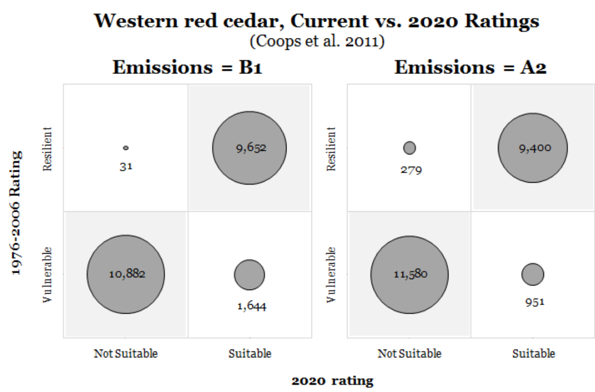
A particularly confounding aspect of these current vulnerability/resilience ratings is the apparent conflict with both near-term and long-term future climate projections of Coops et al. (2011). For example, as shown in Figure Set 3, more than six million acres classified as 'vulnerable' for Western hemlock in 2006 were re-classified as 'suitable' by 2020. For Western redcedar, more than 950,000 acres classified as 'vulnerable' in 2006 were reclassified as 'suitable' in 2020. There is no published explanation for this apparently inconsistent model behavior in the Coops et al. (2011) future projections that predict suitability under climate change at the same time these same areas have already been rated as vulnerable in 2006.

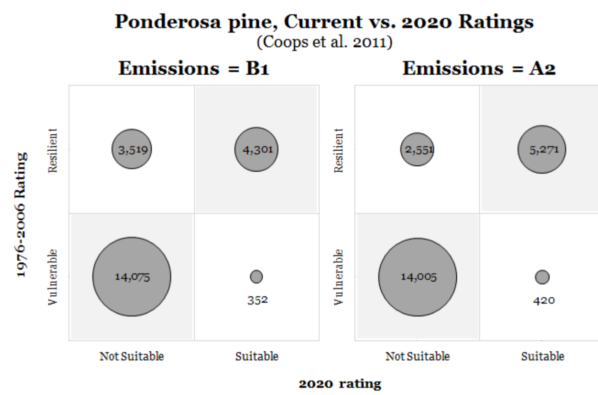
Through further personal correspondence with the authors, we learned that these authors suggest the use of annual averages for future climate suitability ratings are likely driving a more error-prone rating of future climatic suitability due to the absence of monthly climate data. The authors report being "particularly excited about the current stress predictions" of vulnerability/resilience and have published additional research indicating that the current vulnerable ranges identified in their bioclimate envelope research are already showing increased disturbance detected via satellite imagery (Waring *et al.* 2011). Based on these communications, we believe the future climate envelope projections of Coops et al. (2011) suffer from insufficient statistical rigor and fail to provide statistical validation of this same approach used for future suitability projections on current species presence/absence. Together, we believe these significantly question the confidence in their previously published projections of future climate suitability, and that their ratings of current vulnerability/resilience are likely to be more reliable indicators of shifting habitat suitability due to climate change.

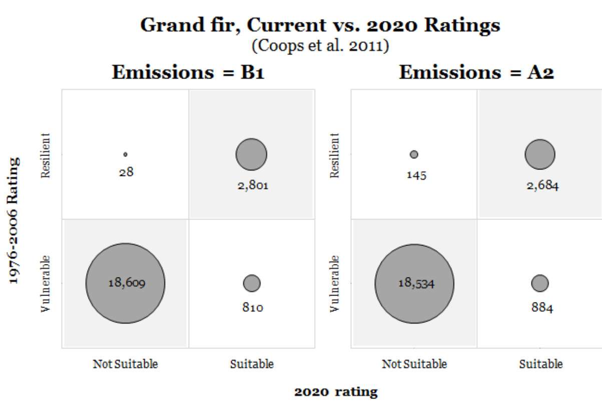
Figure Set 3. Correspondence of Coops et al. 2011 current and future habitat suitability ratings.

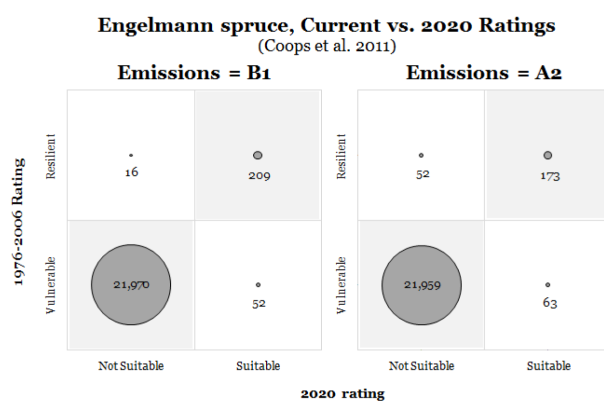






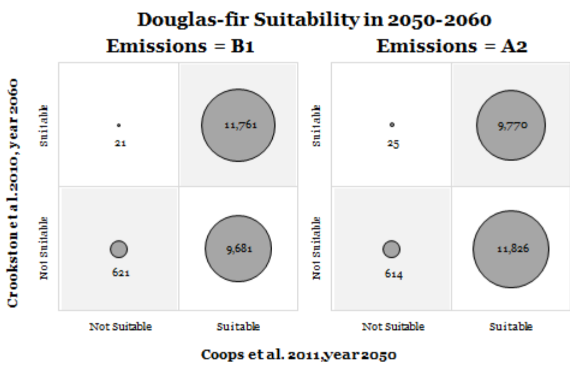


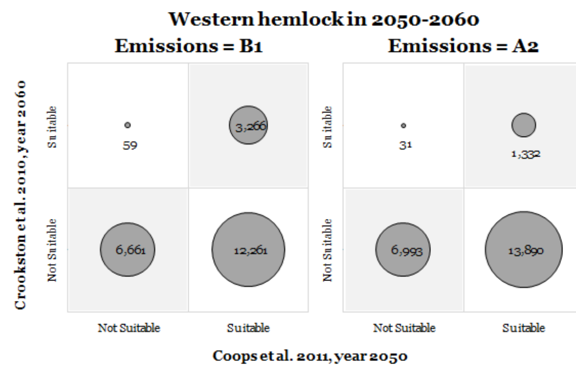


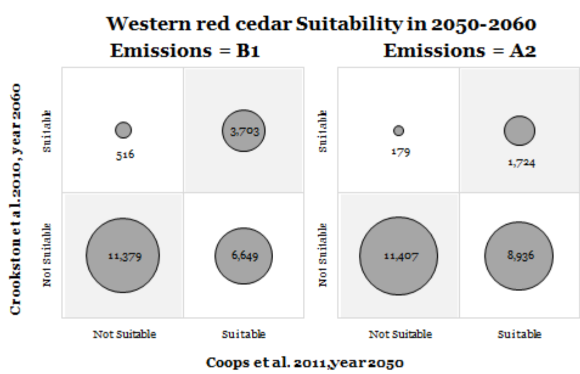


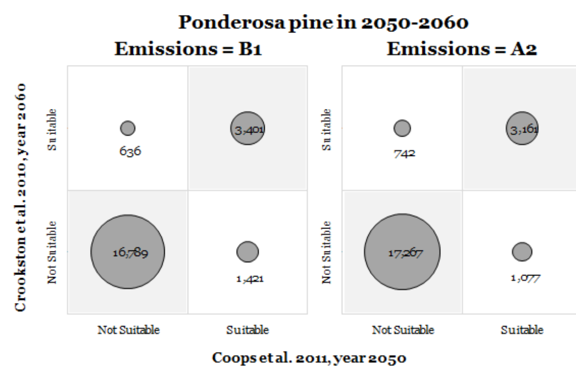
Note: Values inside or below each bubble indicate thousands of acres as classified by the rating systems indicated on the x- and y-axes of each graph.

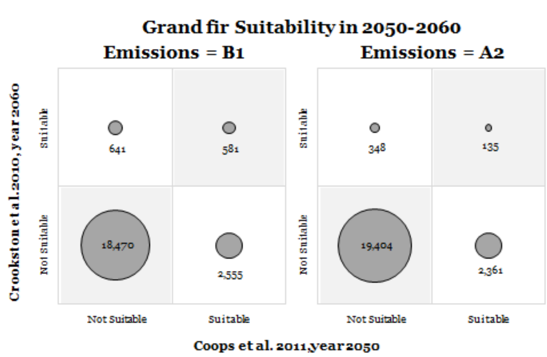
Figure Set 4. **Agreement/Disagreement between Crookston et al. 2010 and Coops et al. 2011 for future climatic suitability for several tree species in 2050-60.**

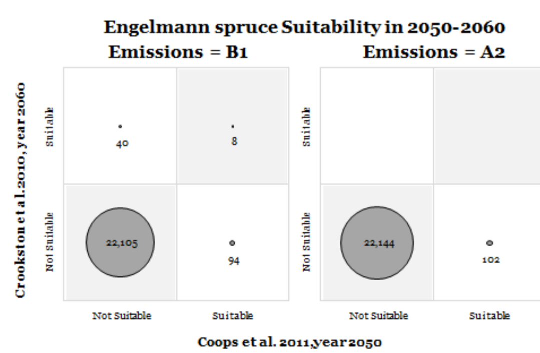












Note: Values inside or below each bubble indicate thousands of acres as classified by the rating systems indicated on the x- and y-axes of each graph.

Future habitat suitability, Coops v. Crookston

The Coops et al. (2011) future bioclimate envelope projections are generally more 'optimistic' in comparison to Crookston et al. (2010) in terms of broad-scale suitability for several species across the extent of BLM's Western Oregon district boundaries. In particular, prominent disagreement is apparent in future projections for Douglas-fir, Western hemlock, and Western redcedar. For example, across the 22.25 million acres of land within the BLM Western Oregon district boundaries, Crookston et al. (2010) project just under 12 million acres as suitable for Douglas-fir under the B1 scenario by 2060 while Coops et al. (2011) project over 21 million suitable acres in 2050.

Maps of future habitat suitability to be used in Climate-FVS modeling

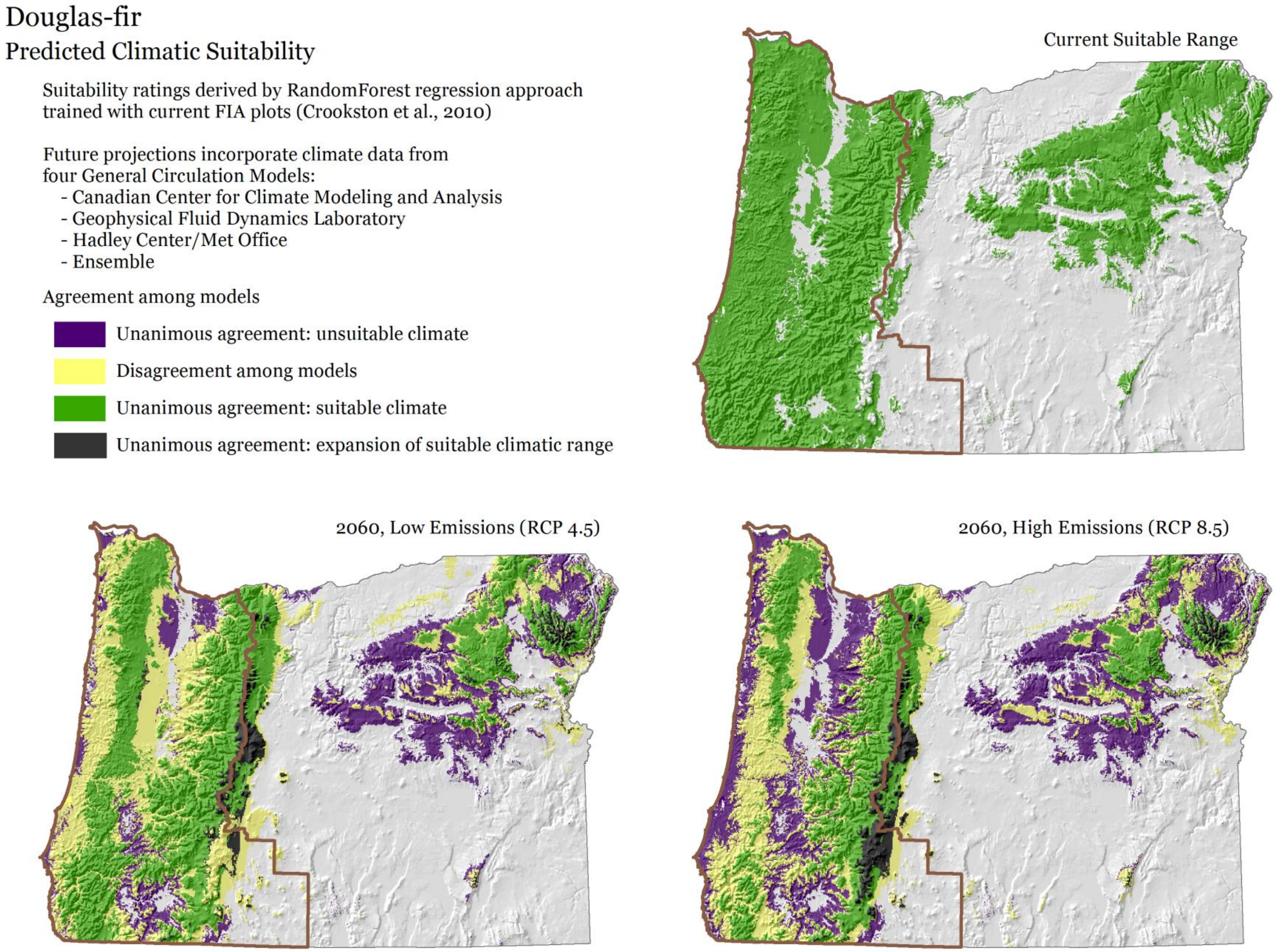
Map Set 2 presents the level of agreement in habitat suitability for each species by 2060 based on climate projections of four different GCMs for each emissions scenario (RCP 4.5 and 8.5). All of the data displayed in these maps were produced by Nicholas Crookston using the process described in Crookston et al. (2010), albeit using updated GCMs and emissions scenarios from CMIP5.

There is generally unanimous agreement across GCMs and emissions scenarios that the climate will remain suitable for Douglas-fir along the Cascade Range, but become unsuitable in the Elkhorn Mountains along the southern and western range of the Blue Mountains in northeastern Oregon, in many locations near the Pacific Coast, and scattered along the I-5 corridor between Roseburg and Medford in southern Oregon. Under the low emissions scenarios, all four GCM's climate projections suggest climatic suitability for Douglas-fir along the Coast Range and into southern Oregon. Under the high emissions scenario, there is disagreement among the models regarding the suitability of the southern extent of the Coast Range and the Klamath Mountains, but unanimous agreement among the models that the coast becomes unsuitable, as well as increased areas of unsuitability along the route from Roseburg to Medford in southern Oregon. The unanimous projection of an expanded range for Douglas-fir along the eastern face of the Cascade Range from central to southern Oregon is present in both low and high emissions scenarios, although the high emission scenario shows a pronounced expansion of Douglas-fir climatic suitability into the BLM Lakeview District.

Western hemlock and Western redcedar show dramatic projected declines in future climatic suitability in both low and high emissions scenarios. These projected declines in suitable climate spread broadly across the Coast Range and the southern extent of these species' historical ranges along the Cascade Range. These projections indicate a northward shift in the climatic conditions suitable for these species along the Cascades.

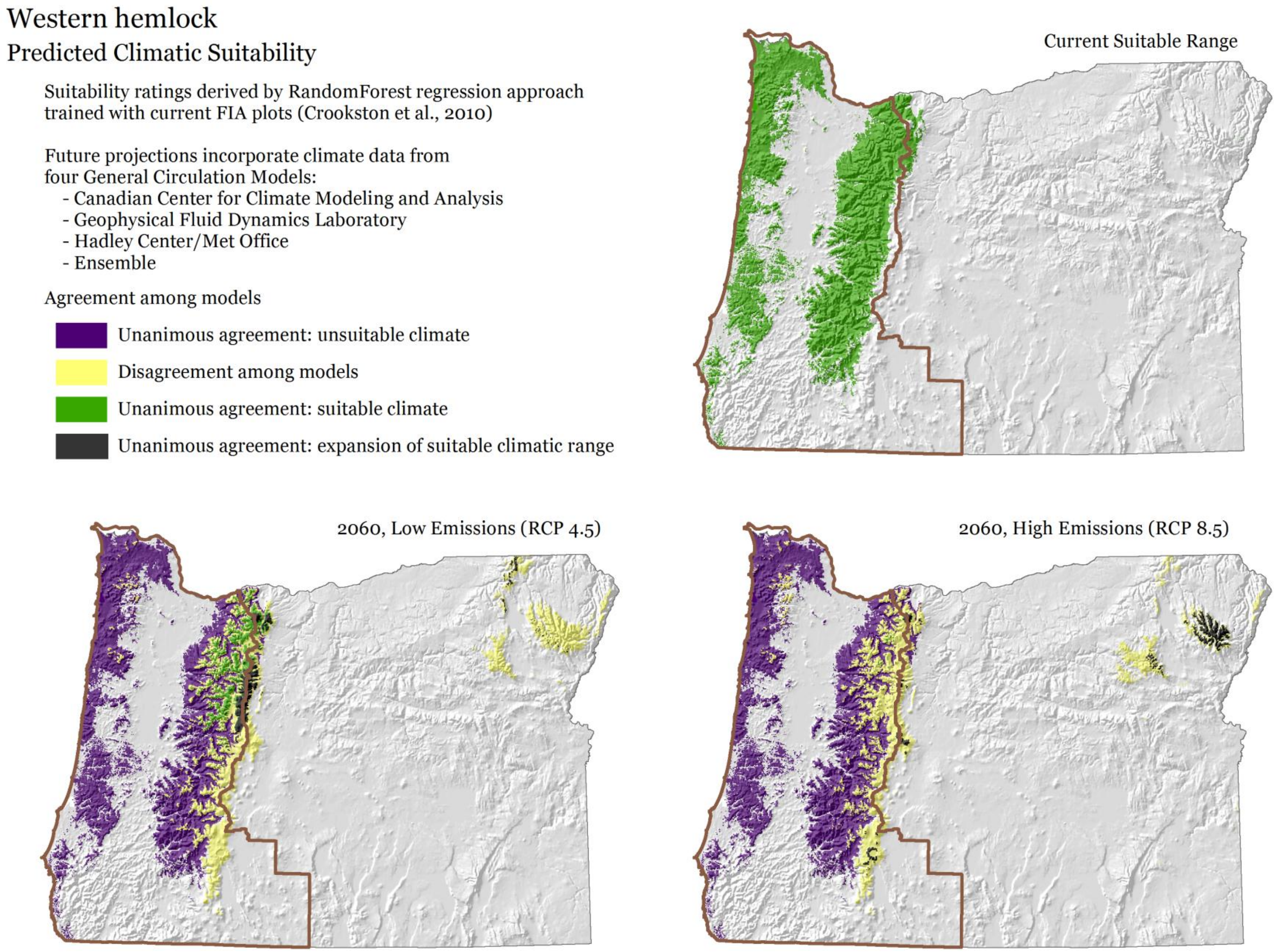
For Ponderosa pine, there is unanimous agreement across climate models that currently suitable areas will remain suitable along the eastern edge of the Cascade Range and the eastern range of the Klamath Mountains in southern Oregon at least through 2060. These models generally agree that future climate will become increasingly unsuitable for Ponderosa pine along the southern extent of the Elkhorn Mountains within the Blue Mountains Range. There is disagreement among the models regarding the suitability for Ponderosa pine in central Oregon south of La Pine. The future climate conditions simulated by all four GCMs unanimously project unsuitable climate for Grand fir and Engelmann spruce throughout these species' current ranges in western Oregon.

Map Set 2: **Future bioclimate envelopes for several tree species**



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, which is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 2 (continued)



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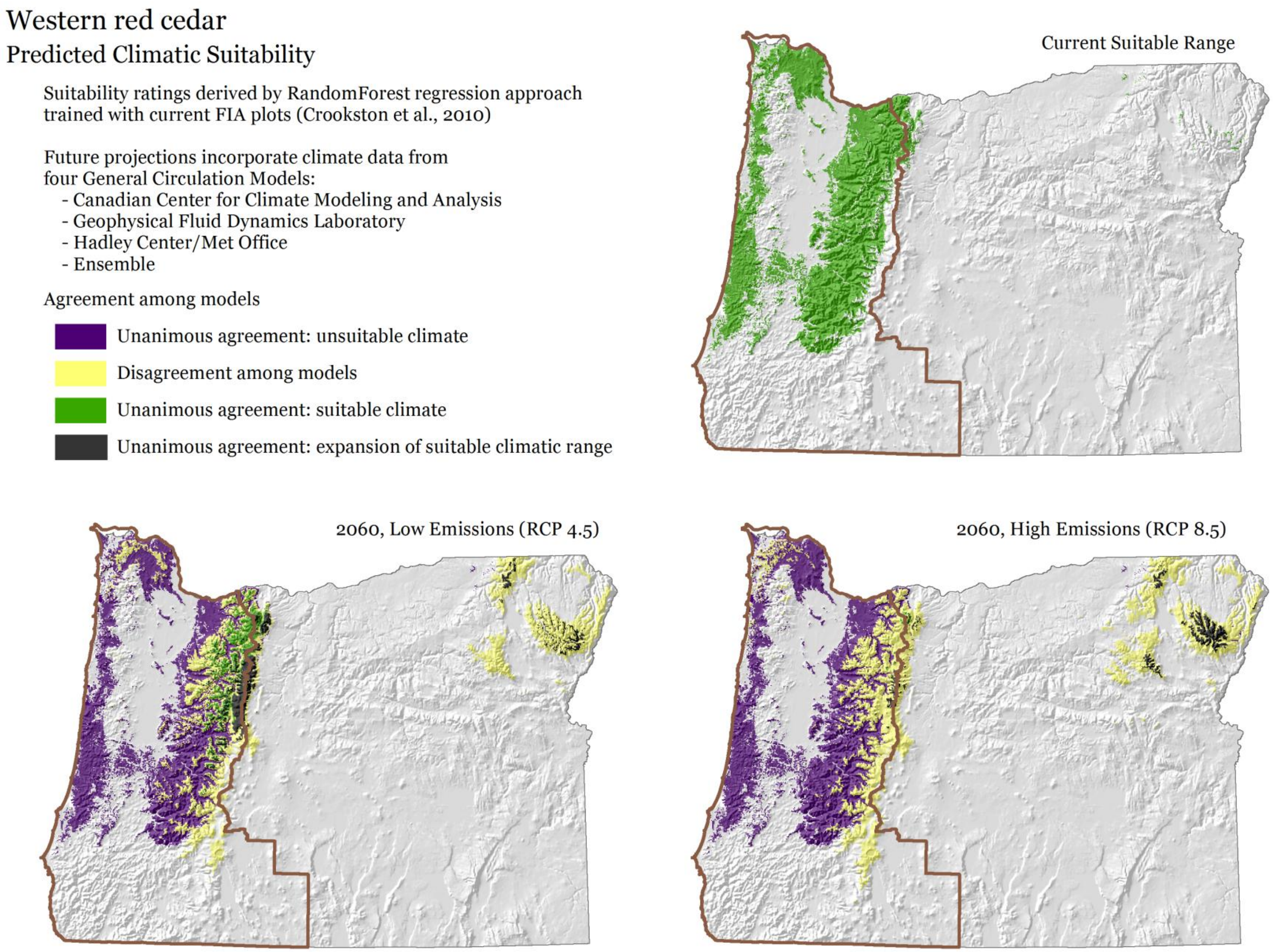
Map Set 2 (continued)



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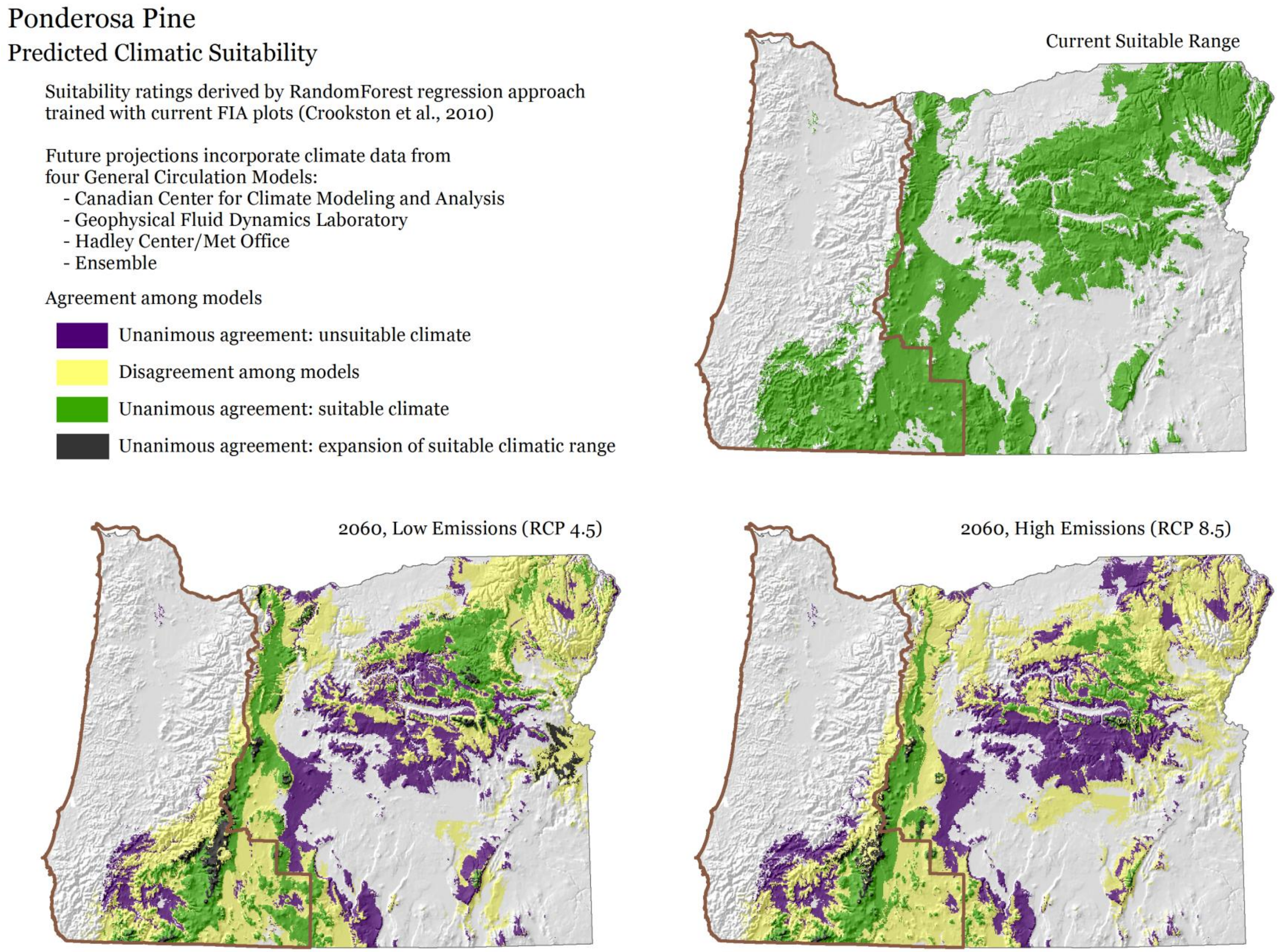
Map Set 2 (continued)



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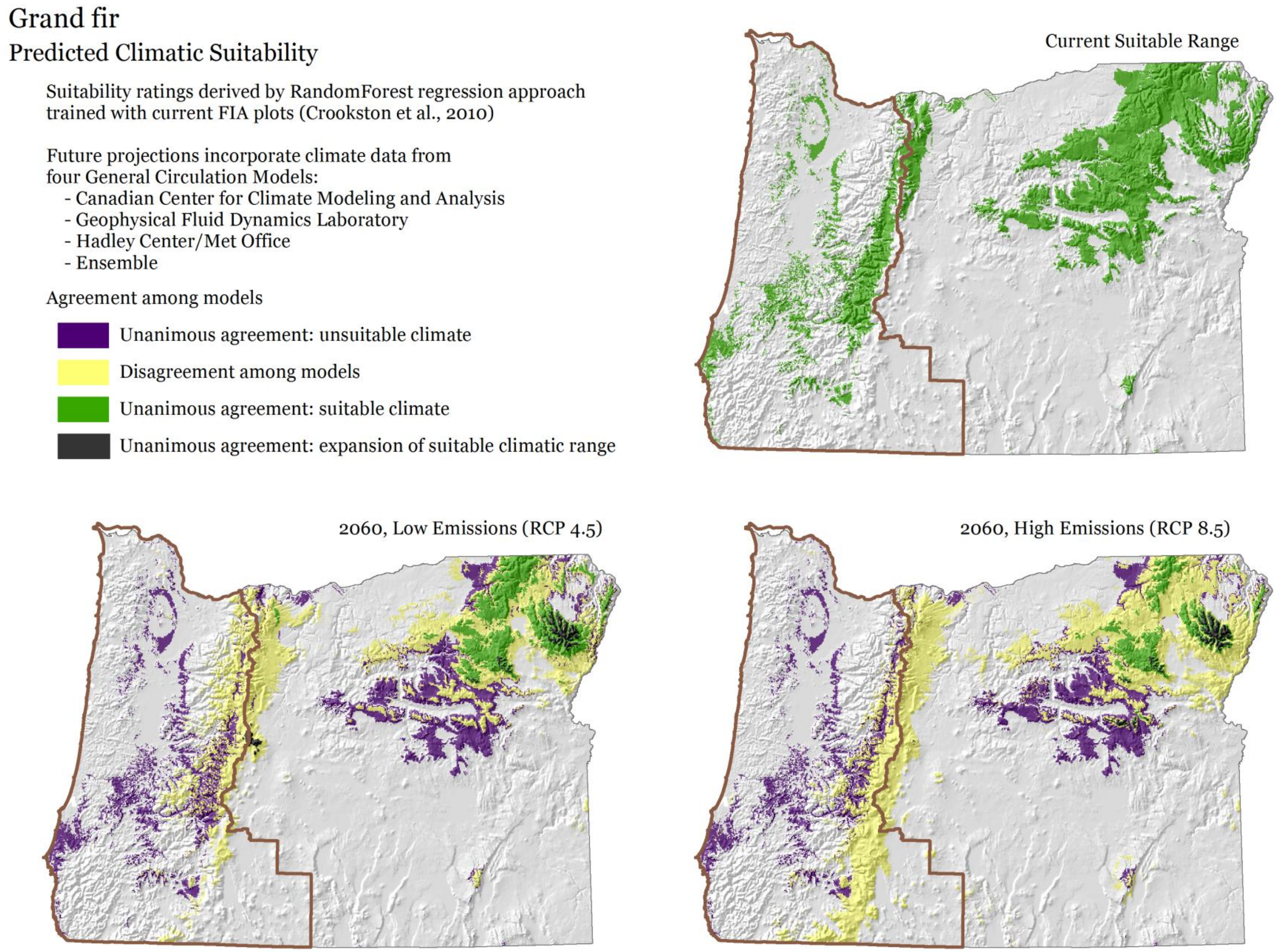
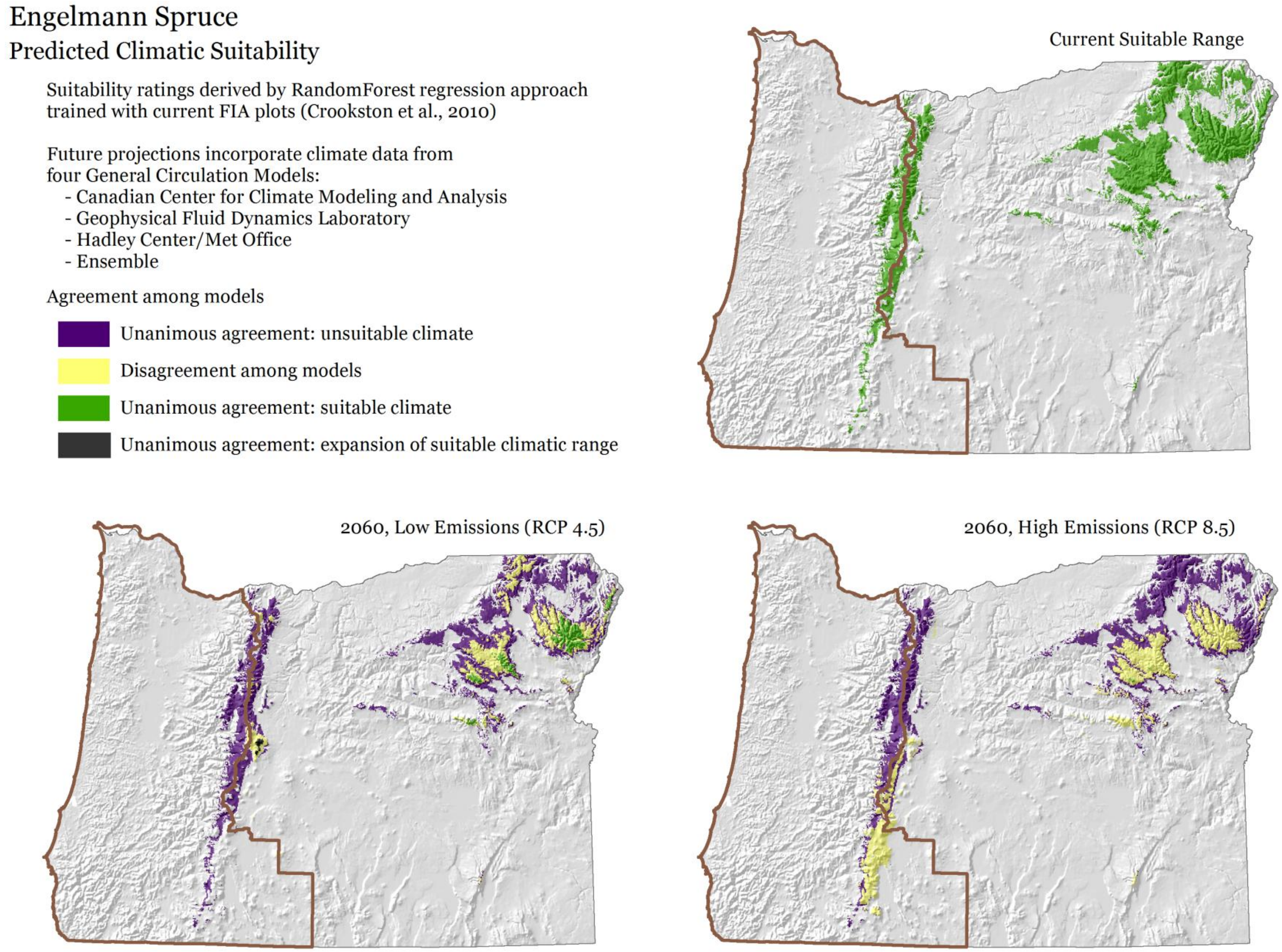
Map Set 2 (continued)



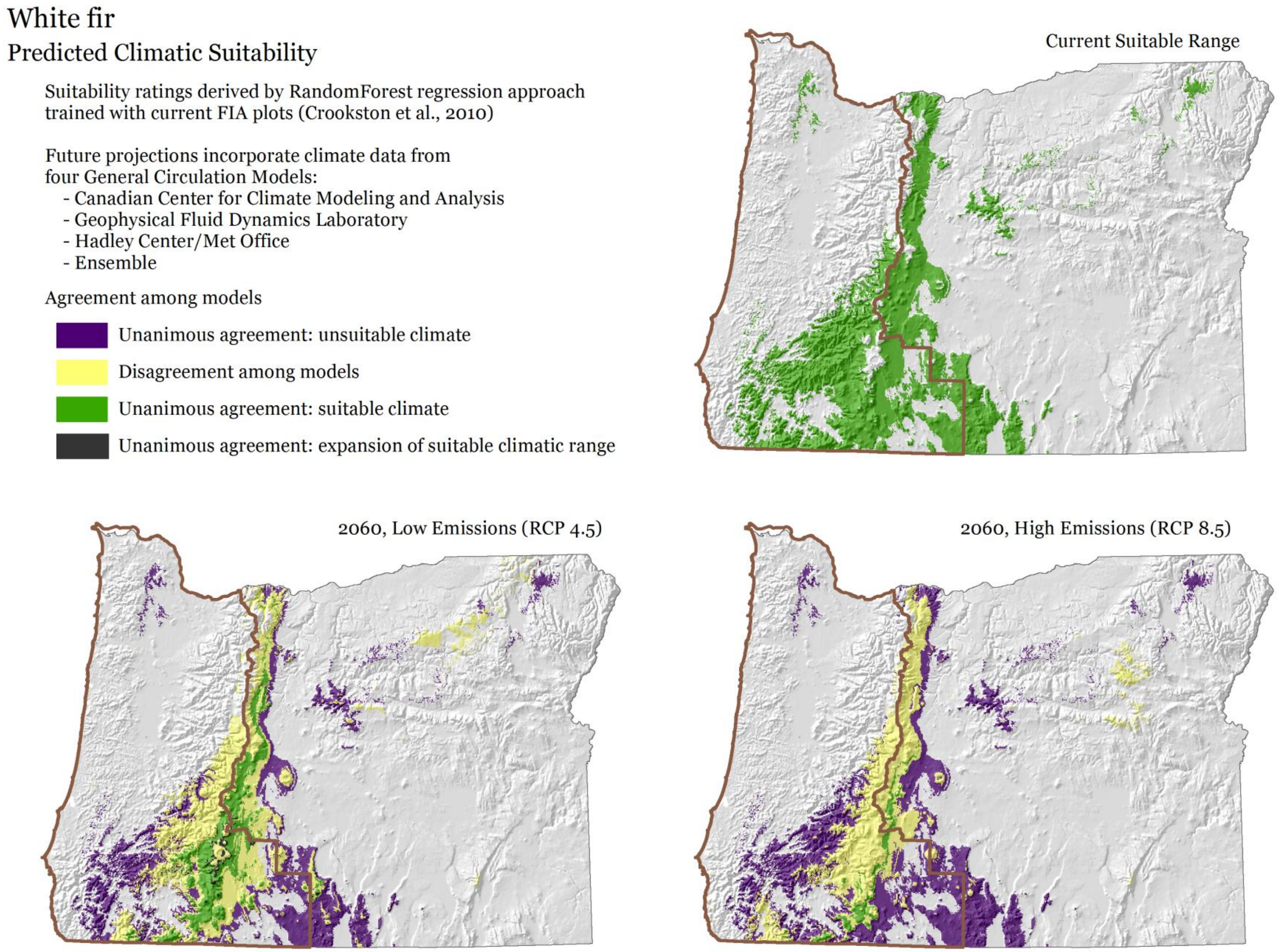
Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, which is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 2 (continued)



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, which is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 2 (continued)



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, which is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

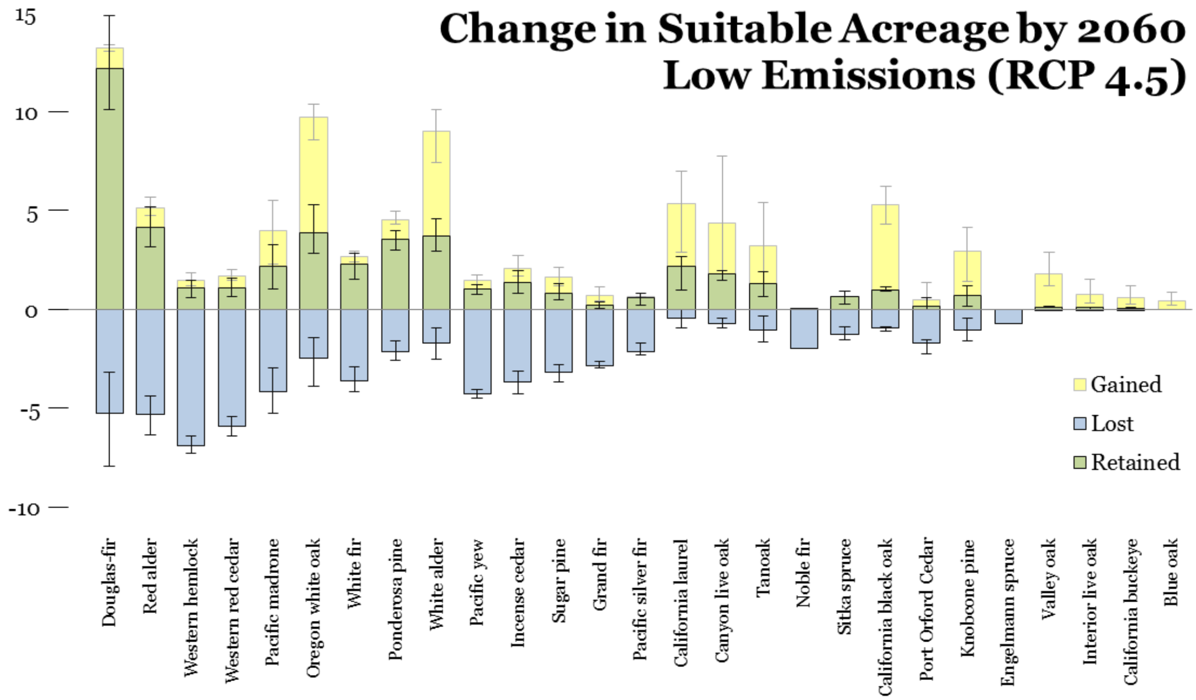
Projected shifts in acreage suitable for many species across western Oregon

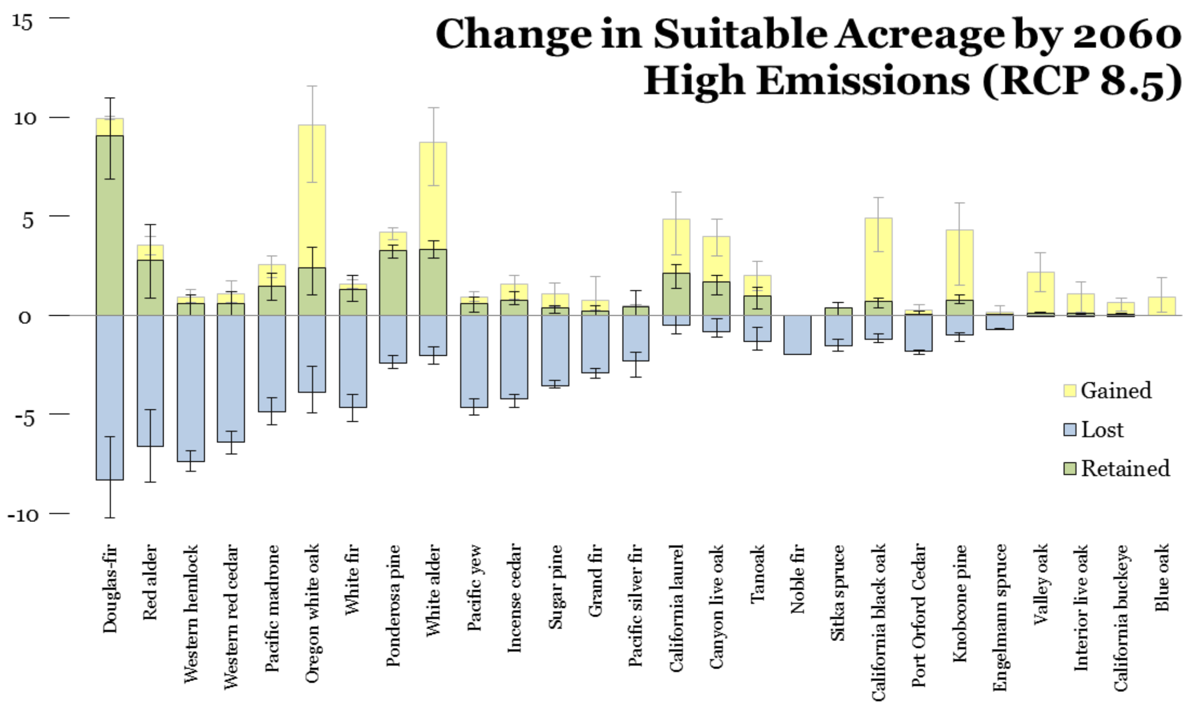
Figure Set 5 provides a broad overview of the projected changes in acreage of habitat suitability in western Oregon for multiple species. Consistent with results reported earlier by McKenney et al. (2007), hardwood species appear to gain millions of acres of climatically-suitable habitat. Several commercially important conifer species are projected to lose the majority of their climatically-suitable ranges within western Oregon, including Western hemlock, Western redcedar, Pacific yew, Incense cedar, and Sugar pine in both low and high emissions scenarios.

Eight hardwood species along with Knobcone pine were projected to experience broad gains in climatically suitable habitat across western Oregon (see Figure Set 5 and Map Set 3). White alder and Oregon white oak both showed substantial areas along the east side of the Coast Range that were unanimously projected to become suitable by 2060. California laurel, Knobcone pine, and Canyon live oak showed disagreement among models, but had one or more projecting newfound suitability along the Willamette Valley and Coast Range.

Some of these species show non-linear responses to climatic suitability based on emissions scenarios. For example, under the low emissions scenario, there was virtually no unanimous projection of expanded suitability for Knobcone pine, but in the high emissions scenario, Knobcone pine was unanimously projected to have newly suitable range on the western Klamath Mountains; in contrast, California laurel was projected unanimously to have new suitable range in the western Klamath Mountains under the low emissions scenario, but not in the high emissions scenario.

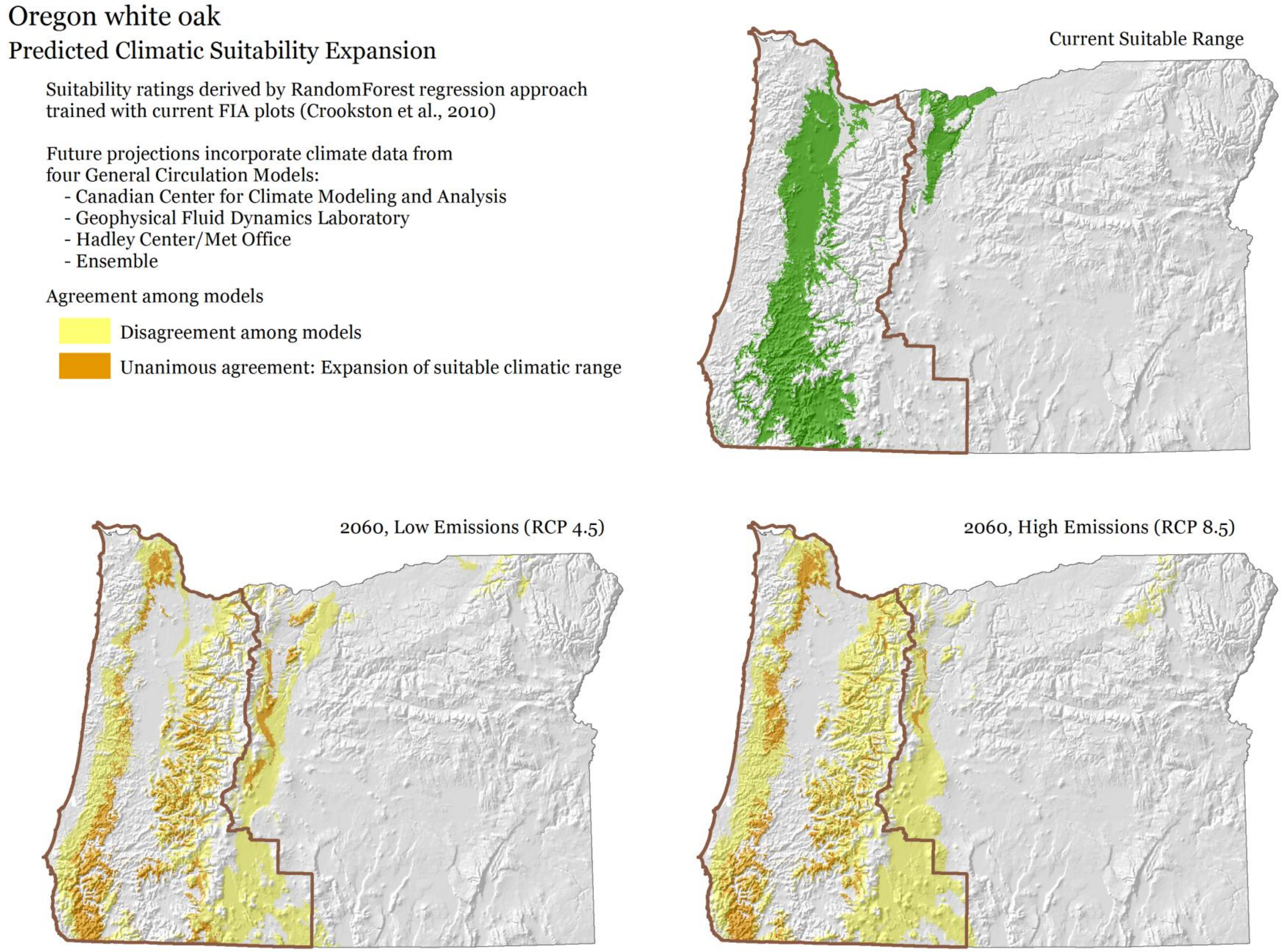
Figure Set 5: **Change in bioclimate envelopes for several tree species within western Oregon BLM district boundaries**





Note: Bars represent the average across four general circulation models (GCMs), in millions of acres. Error bars indciate the minimum and maximum change estimated among these GCMs.

Map Set 3: Projected expansion of climatic suitability beyond historical range for several species



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 3 (continued)

White alder

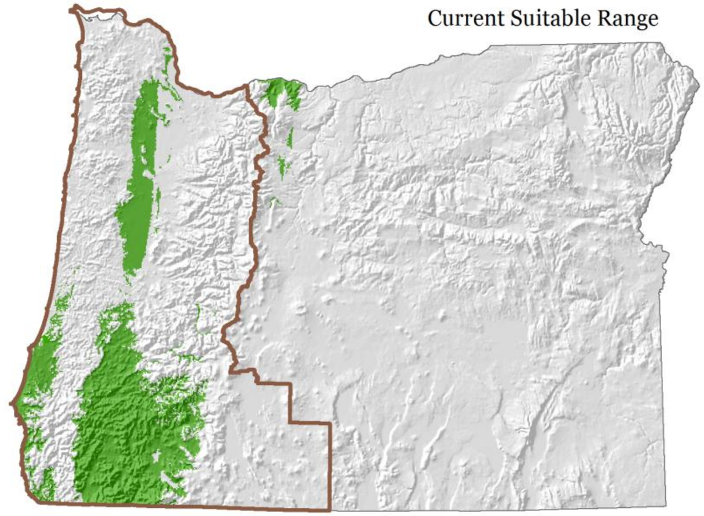
Predicted Climatic Suitability Expansion

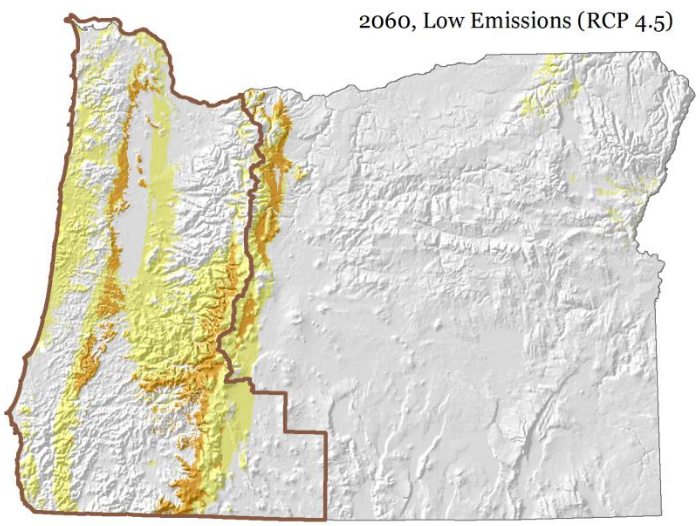
Suitability ratings derived by RandomForest regression approach trained with current FIA plots (Crookston et al., 2010)

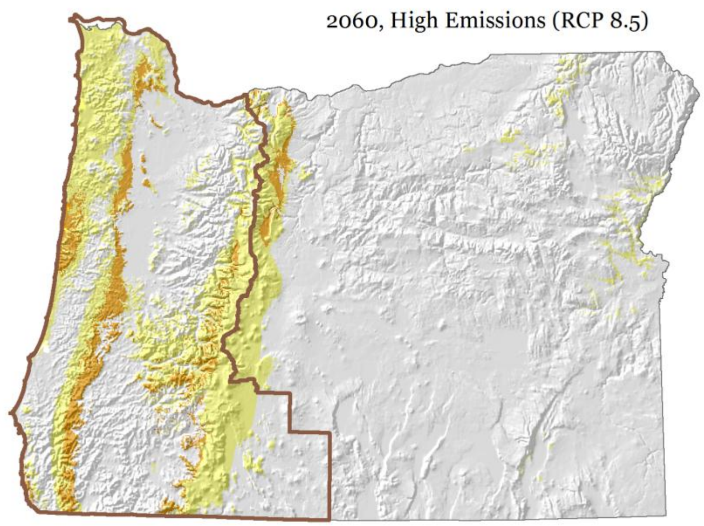
Future projections incorporate climate data from four General Circulation Models:
- Canadian Center for Climate Modeling and Analysis
- Geophysical Fluid Dynamics Laboratory
- Hadley Center/Met Office
- Ensemble

Agreement among models

- Disagreement among models
- Unanimous agreement: Expansion of suitable climatic range

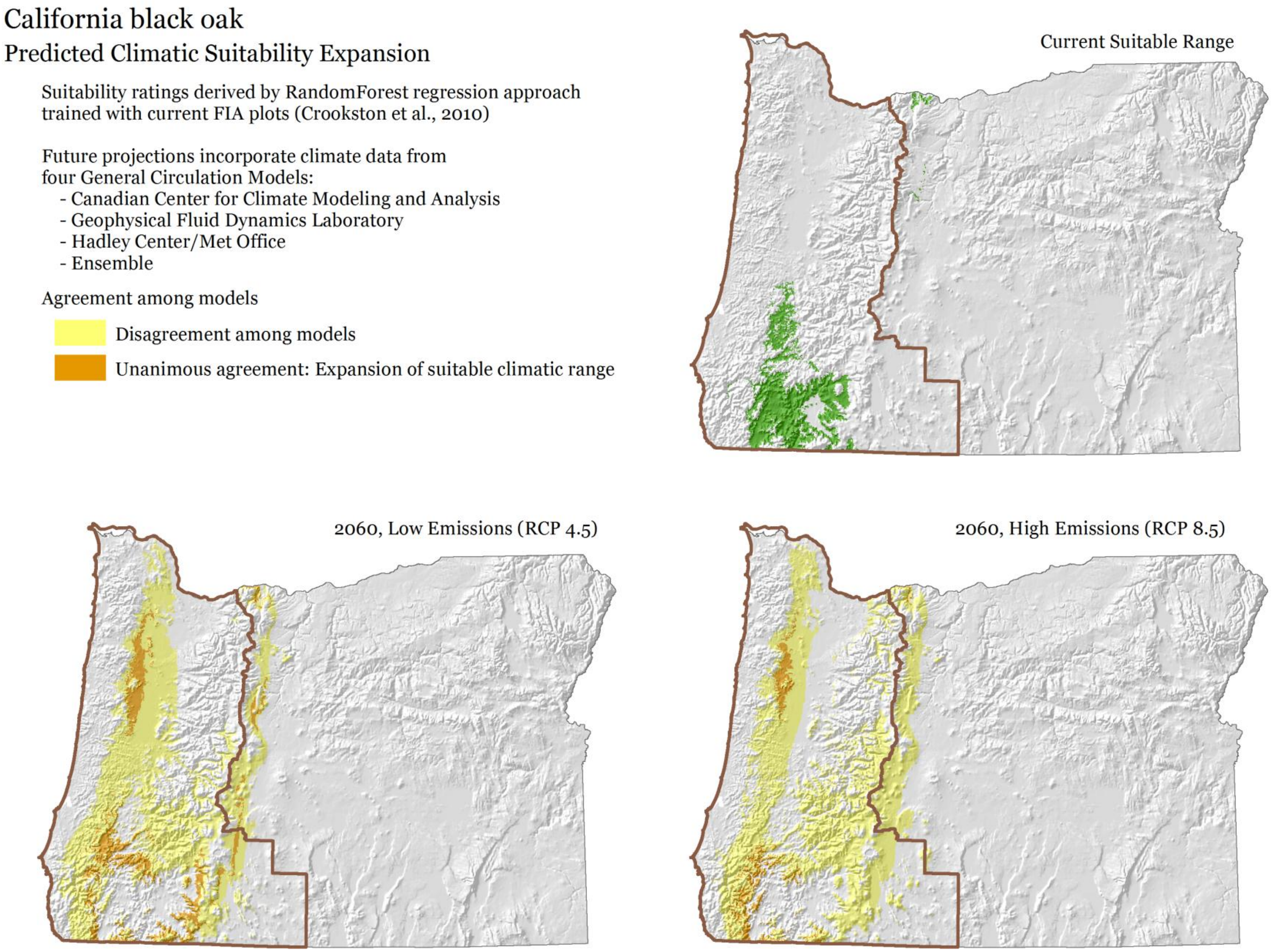






Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 3 (continued)



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 3 (continued)

Knobcone pine

Predicted Climatic Suitability Expansion

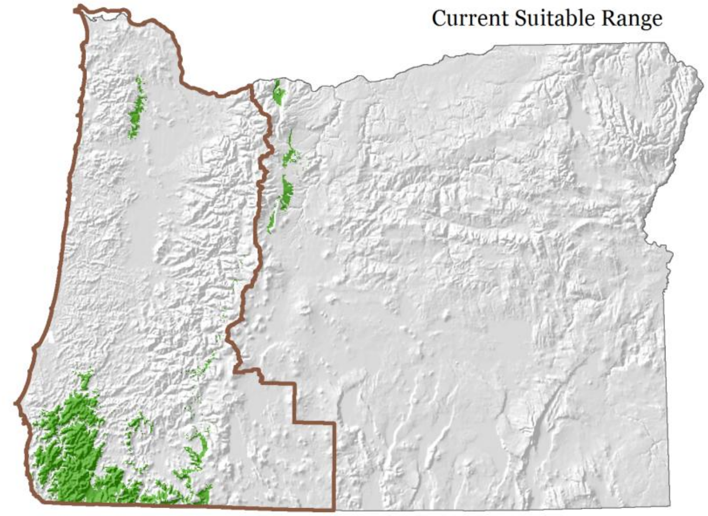
Suitability ratings derived by RandomForest regression approach trained with current FIA plots (Crookston et al., 2010)

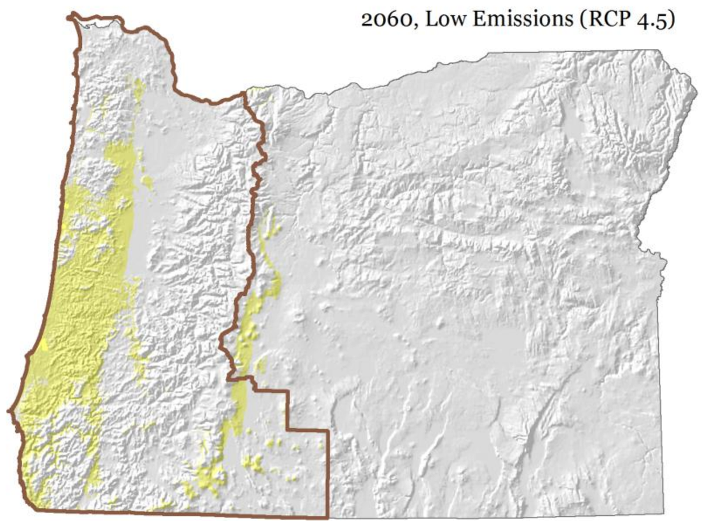
Future projections incorporate climate data from four General Circulation Models:
- Canadian Center for Climate Modeling and Analysis
- Geophysical Fluid Dynamics Laboratory
- Hadley Center/Met Office
- Ensemble

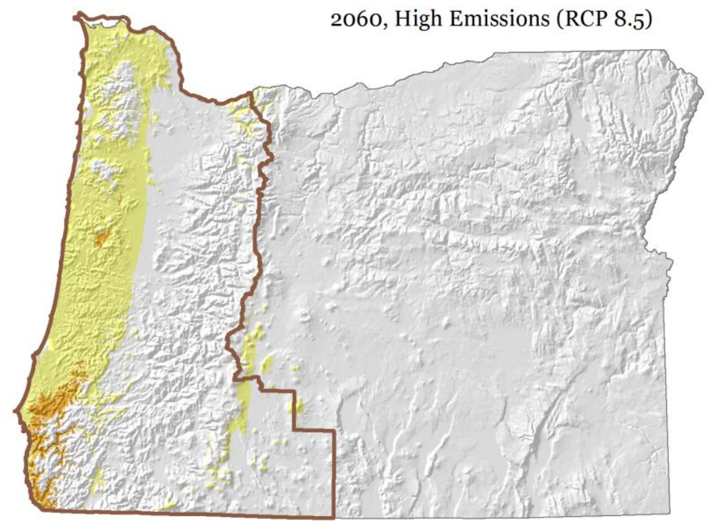
Agreement among models

Disagreement among models

Unanimous agreement: Expansion of suitable climatic range

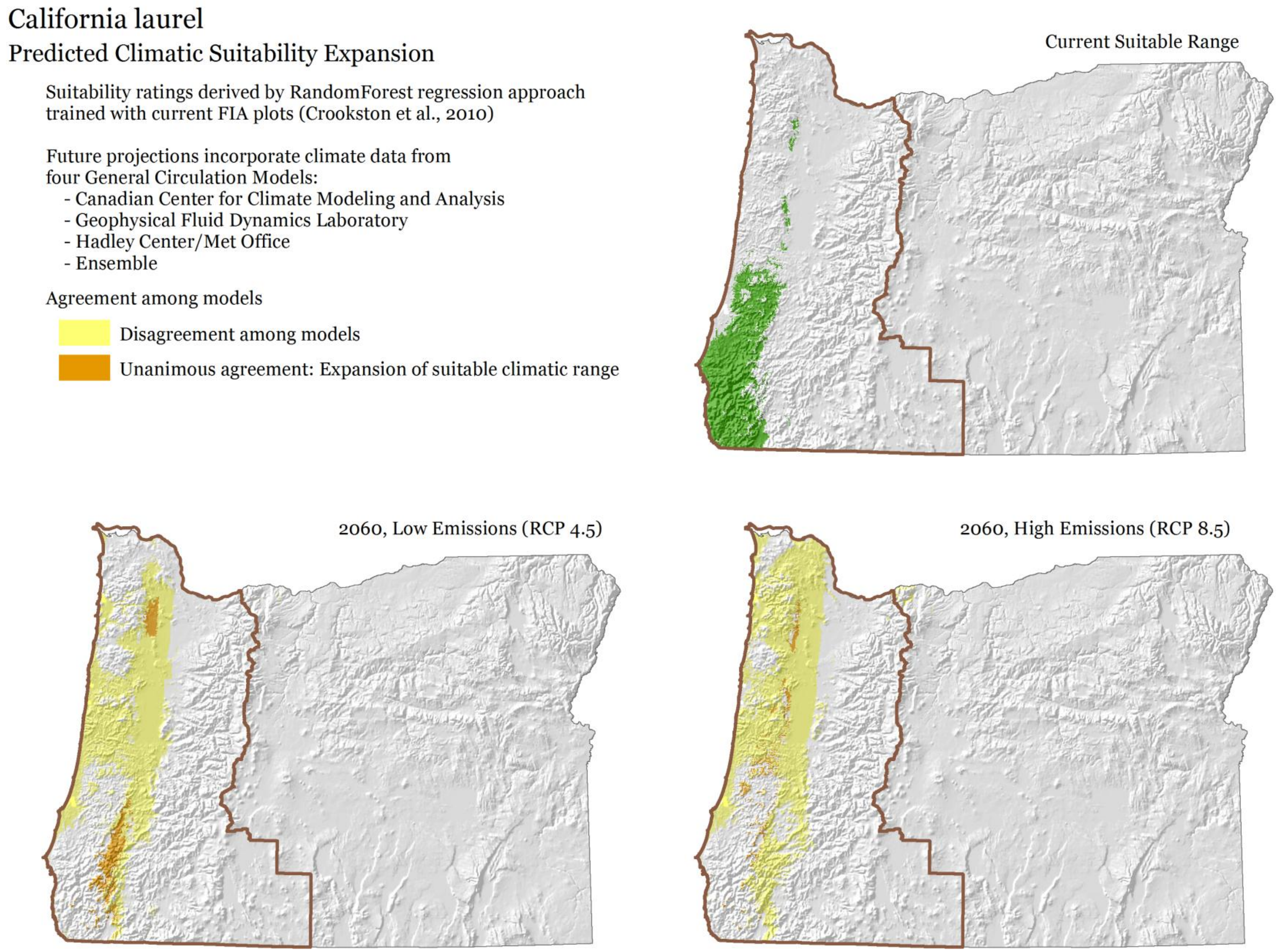






Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 3 (continued)



Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Map Set 3 (continued)

Canyon live oak

Predicted Climatic Suitability Expansion

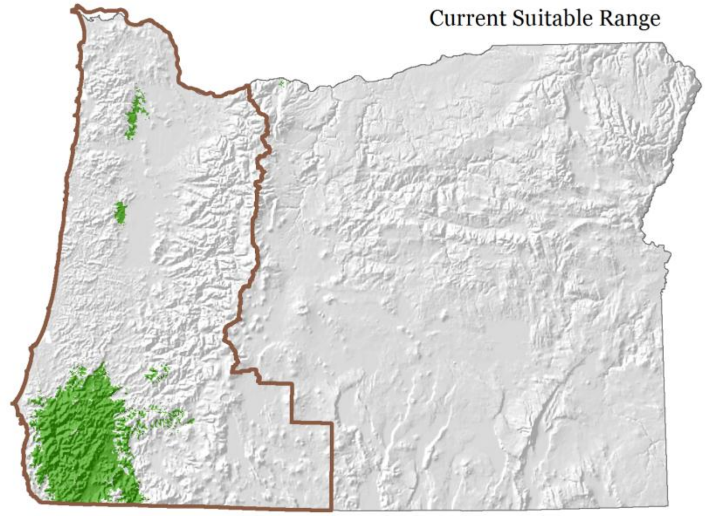
Suitability ratings derived by RandomForest regression approach trained with current FIA plots (Crookston et al., 2010)

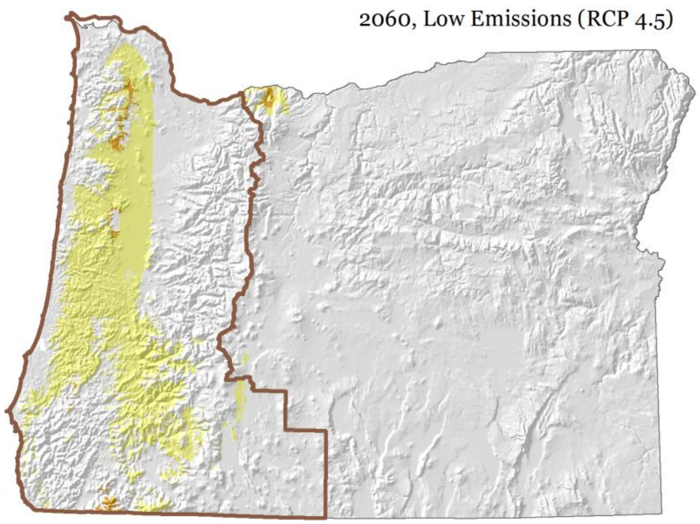
Future projections incorporate climate data from four General Circulation Models:

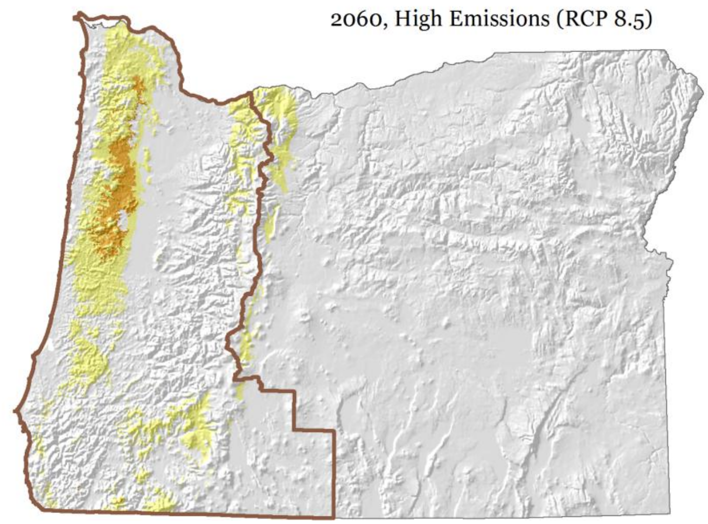
- Canadian Center for Climate Modeling and Analysis
- Geophysical Fluid Dynamics Laboratory
- Hadley Center/Met Office
- Ensemble

Agreement among models

- Disagreement among models
- Unanimous agreement: Expansion of suitable climatic range







Note: These maps do not represent predicted future species distributions. *These maps show future climatic suitability, specifically for areas that are currently modeled as climatically unsuitable for the species. Climatic suitability is one of several factors that affect species distributions. These maps help answer the question: "How similar are future climatic conditions in each location to the places where a species currently grows?" Changes in climatic suitability should be expected to affect the growth and/or mortality of species over time by interacting with many other important environmental and physiological factors not represented here.*

Maps of future potential vegetation types by MC2

Map Set 4 shows the most commonly chosen forested potential vegetation type for each pixel on the map among the 10 different GCMs evaluated in the MC2 study. The projections of future potential vegetation types from 2035-2060 by MC2 are fairly similar under both the low (RCP 4.5) and high (RCP 8.5) emissions scenarios. In general, MC2 projections suggest broad shifts in potential vegetation types across Oregon. Subalpine forest is expected to nearly disappear across the state, with small areas in the Blue Mountains and the Cascade Range remaining by 2060. Maritime evergreen needleleaf forests are projected to shift northward and be replaced in their southern extent by temperate cool mixed forests. The range of temperate evergreen needleleaf forests is expected to expand beyond current distributions along the Cascade Crest further eastward and southward toward the Klamath Basin and southwest into the Klamath Mountains, as well as south and westward from the Blue Mountains in northeastern Oregon. These areas of expansion for temperate evergreen needleleaf forest are projected to occur as areas that are currently non-forest shift to become suitable for forest vegetation. Along the southwest Oregon Coast, temperate cool mixed forests are expected to be increasingly suitable for replacement by subtropical mixed forests.

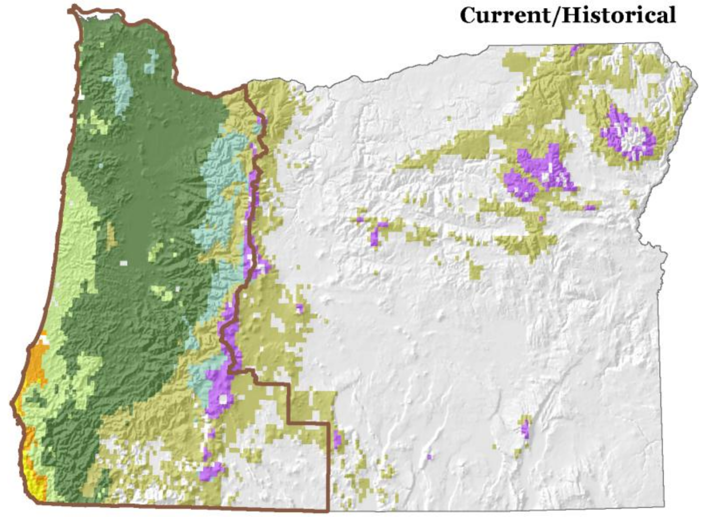
Map Set 5 shows the level of agreement among projections from the 10 GCMs evaluated by MC2 as to whether a change from the current/historical forested potential vegetation types is observed by 2060. The most densely clustered zones of unanimous agreement of vegetation type changes are found in southwestern Oregon running from the coast through the Klamath Mountains and the southern extent of the Cascade Range. Additional hotpots where vegetation type change is projected unanimously can be observed ringing the eastern edge of the Willamette Valley where maritime evergreen needleleaf forests are expected to give way to temperate cool mixed forest. Areas where a majority of GCMs led to projected vegetation type changes (as opposed to unanimous) are spread broadly throughout the Willamette Valley and southwestern Oregon. Along the eastern flank of the Cascade Range and in the Blue Mountains, there was commonly unanimous projection of retention of the current temperate evergreen needleleaf forest.

Map Set 4

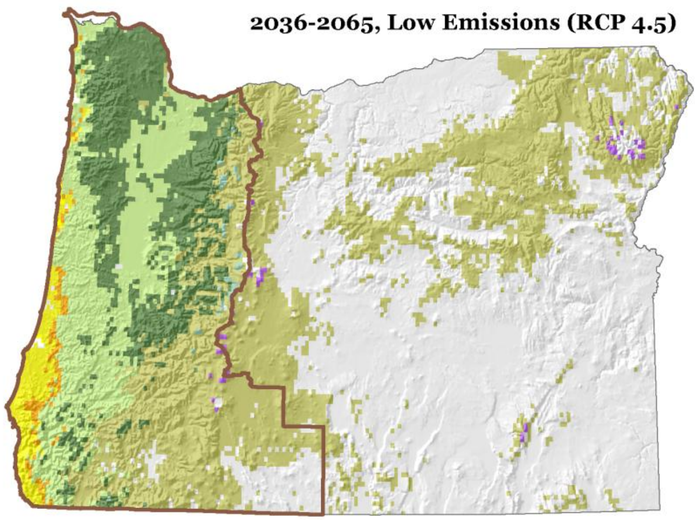
MC2: Potential Shifts in Forest Vegetation

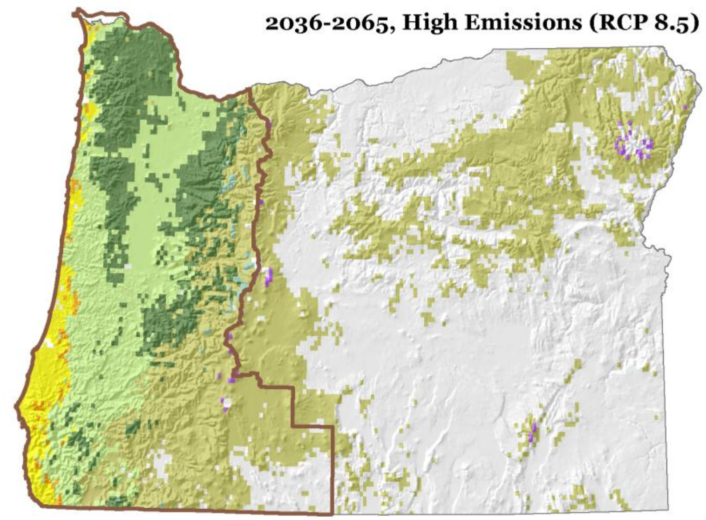
Forest Vegetation Types

- Subalpine Forest
- Maritime Evergreen Needleleaf Forest
- Temperate Evergreen Needleleaf Forest
- Temperate Cool Mixed Forest
- Temperate Warm Mixed Forest
- Subtropical Mixed Forest
- Cool Needleleaf Forest



Future Potential Vegetation Types represent the majority type predicted by MC2 simulations of 10 GCMs (Bachelet, 2014)

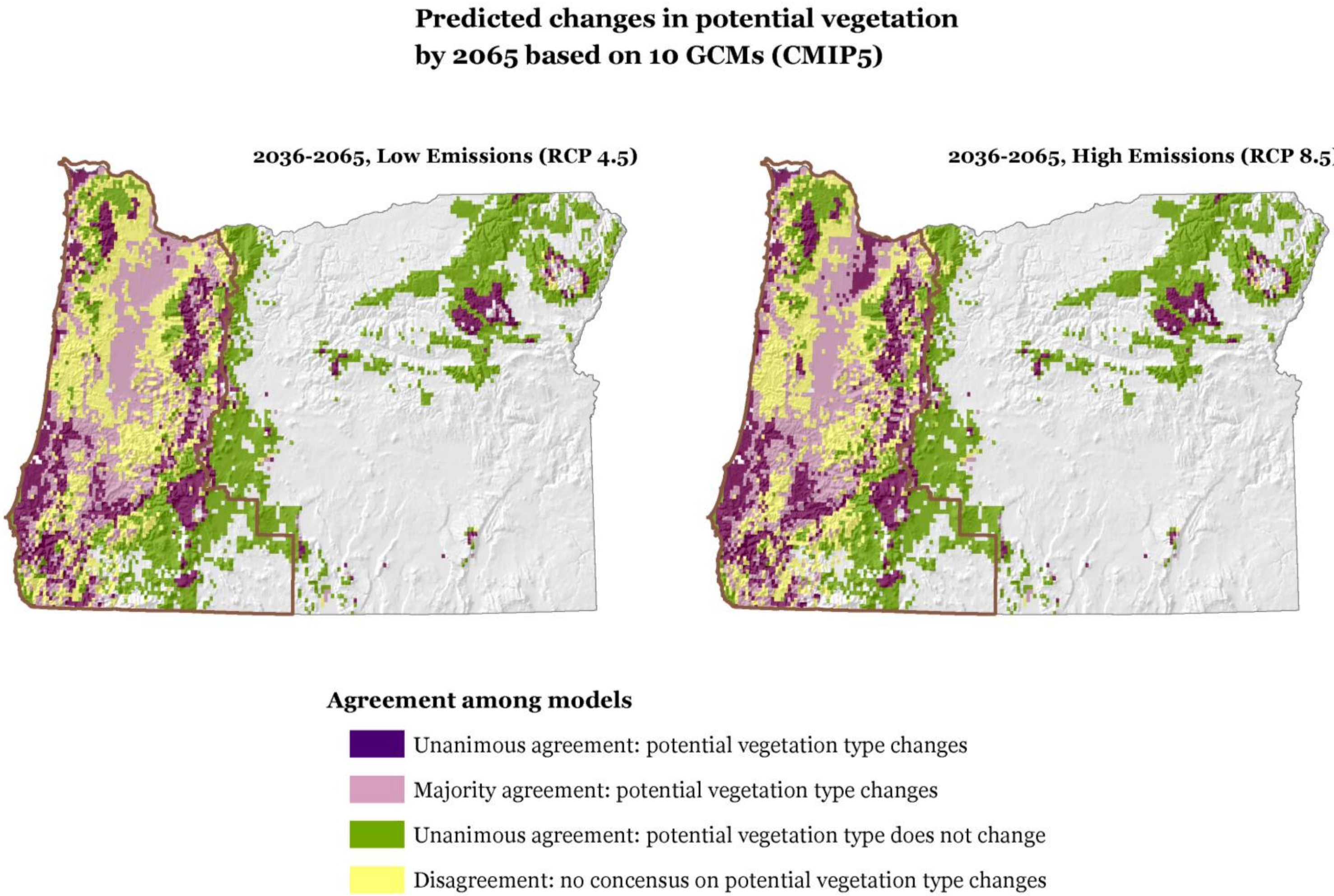




Note: These maps do not represent predicted future species distributions. *These maps show the most commonly predicted Potential Vegetation Type by the MC2 Dynamic Global Vegetation Model across 10 different GCMs. These maps may be helpful for identifying geographic locations where climate change is expected to introduce conditions that are better suited for different types of vegetation than currently exist. Only those areas classified as forested potential vegetation types are shown, all other potential vegetation types have been hidden from display.*

Map Set 5

MC2: Shifts in Potential Vegetation



Data from Bachelet (2014)

Note: These maps do not represent predicted future species distributions. *These maps show the level of agreement in projected change to current Potential Vegetation Types by the MC2 Dynamic Global Vegetation Model across 10 different GCMs under low and high emissions scenarios. These maps may be helpful for identifying geographic locations where climate change is expected to introduce conditions that are better suited for different types of vegetation than currently exist. The level of agreement shown here only reflects areas that are currently/historically classified as forest, all other potential vegetation types have been hidden from display.*

Discussion

Assessing confidence in estimates of current climatic suitability

The Random Forests approach applied by Crookston et al. (2010) more tightly fits current presence/absence data from forest inventory plots; however, the tightness of fit also suggests that areas with suitable climates where that species has not been observed in FIA data may be omitted from current and future bioclimate envelopes. This aspect of Random Forests seems likely to increase the emergence of a bias towards overly-sensitive or pessimistic future bioclimate envelopes, particularly in cases where the future climatic variables fall outside the range observed historically and where the species has been documented in FIA plots.

Random Forests and similar statistical approaches will interpret species absence in FIA training data as being climatically-driven. For example, in areas such as the Willamette Valley, FIA plots where Douglas-fir are not observed are used to build regression trees that would extrapolate climatic unsuitability for Douglas-fir in other areas where similar climate variables occur where FIA plot data is not available. Since species presence/absence is also driven by additional variables beyond climatic conditions alone (e.g., agricultural land-use in the Willamette Valley), the interpretation of this region as being climatically unsuitable for Douglas-fir contrasts with common knowledge that Douglas-fir is indeed observed throughout this area and that the climate is indeed suitable for its growth. In future projections, if/when any other locations come to resemble the climatic conditions of the Willamette Valley, Random Forests and similar purely statistical approaches will map those areas as climatically unsuitable. We believe there is likely to be a substantial amount of 'false negatives' introduced in this approach to training regression models, and that this behavior likely contributes to the over-prediction of future climatic unsuitability for several species. This tendency in purely statistical models is confirmed by studies that have compared their projections with those of process-based models (Morin & Thuiller 2009; Rowland *et al.* 2011; Cheaib *et al.* 2012).

The estimation of current climatic resilience/vulnerability by Coops et al. (2011) and Coops and Waring (2011) show broader ranges of climatic suitability than Crookston et al. (2010) that go beyond the range of observed species presence/absence seen in FIA plots, but this expanded range is consistent with the recognition that the Coops approach models the *fundamental* niche for these species while Crookston models the *realized* niche for these species.

Methodological concerns for Coops bioclimate envelope projections

The application of physiological mechanistic models to project future bioclimate envelopes offers great promise as an alternative or complement to statistical models. Nevertheless, the hybrid approach as applied by Coops et al. (2011) for future bioclimate envelope projections (in contrast to the approach they use for current vulnerability/resilience) appears to be significantly limited by the use of annual average climate data, the use of individual years to make projections, and the application of only one decision tree per species to project climatic suitability or unsuitability . This approach to future projections deviates substantially from the methodology described for historical and current projections of suitability for which model validation data were reported in Coops et al. (2009) and Coops et al.

(2011). Two lines of evidence draw into question the confidence of the future bioclimate envelope projections of Coops et al. (2011):

- First, areas identified as vulnerable in 2006 to climate change have since seen increased disturbance as reported by Waring et al. (2011), indicating that these vulnerability ratings do offer meaningful insights into the observed vulnerability of forest in these areas.
- Second, there is an apparent inconsistency of current vulnerability estimates with future suitability ratings (i.e., many areas identified as currently vulnerable are shown in future high emissions scenarios as suitable). This inconsistency is particularly apparent for Western hemlock and Western redcedar as shown in Figure Set 3.

Taken together, these concerns raise strong doubts over the usefulness of the future bioclimate envelope projections published by Coops et al. (2011) for drawing inferences about the ongoing and expected shifts in suitable ranges for these species under climate change. These methodological issues do not extend to the ratings of current vulnerability (Coops & Waring 2011) or historical ranges (Coops *et al.* 2009, 2011), which are consistent with the methods and validation statistics reported.

Broad changes project for climatic suitability for many tree species

Widespread losses of climatic suitability for several species

The current projections of vulnerability for tree species by Coops and Waring (2011) as well as the future projections of Crookston et al. (2010) both suggest significant changes in the acreage suitable for several ecologically and commercially important tree species across western Oregon.

Projections of future broad scale vulnerability for several tree species and that many areas are already vulnerable based on already observed changes in climate from historical conditions are consistent with reports of widespread mortality experienced by trees of all ages around the US West (van Mantgem *et al.* 2009) as well as observations of increased disturbance in areas projected to be climatically vulnerable using bioclimate envelope modeling (Waring *et al.* 2011). Nevertheless, it is still important to recognize that while shifts in climatic suitability may correspond to less favorable growing conditions and potentially to increased mortality of particular tree species, these projections do not directly translate into predictions of species presence or absence, as there are a variety of factors including disturbance, human land-use, and others that also affect the distribution of species that are not captured in these models.

The most dramatic projections displayed in this report appear for Western hemlock and Western redcedar. Although the future projections of Crookston et al. (2010) are more pessimistic, the ratings of vulnerability by 2006 of Coops and Waring (2011) bolster support for the expectation that the southern range of these species is likely to be under increasing pressure due to climate change. These findings are also generally consistent with the northward movement of climatically-suitable zones observed by McKenney et al. (2007, 2011). The projections of climatic vulnerability for Western hemlock and Western redcedar, particularly in southwestern Oregon, are consistent with the relatively high rating of habitat affinity risk factors reported by Devine et al. (2012), as well as the bioclimate envelope projections of GEOS Institute (2013) using CMIP3 climate projections, and the significant shifts in potential vegetation types projected by the MC2 model in this area.

Divergence of statistical and mechanistic models consistent with other studies

Several recent studies comparing statistical/empirical approaches like Random Forests with process-based models have concluded that statistical approaches are prone to estimating greater shifts in climatic suitability compared to process-based models and should thus be interpreted cautiously (Morin & Thuiller 2009; Rowland *et al.* 2011; Cheaib *et al.* 2012).

In general, the findings in this report that the statistical model of Crookston et al. (2010) is more pessimistic in terms of projected loss of suitable habitat than the hybridized mechanistic model of Coops et al. (2009, 2011) are consistent with several reports in the literature that have found similar relationships between statistical and mechanistic models (Morin & Thuiller 2009; Keenan *et al.* 2011; Cheaib *et al.* 2012). However, it is worth noting that one of the primary drivers of greater retention of climatically suitable habitat by mechanistic models in these studies was the incorporation of CO_2 fertilization effects on trees. This effect is not captured in the hybridized mechanistic model utilized by Coops et al. (2009, 2011).

Further, it is also worth noting that the hybrid approach of Coops et al. (2009, 2011) does not technically apply mechanistic modeling of habitat suitability by directly incorporating future climatic variables into a process-model; instead, their approach applies a simple statistical decision-tree to future climate data based on correlative relationships derived from process-modeling of historical climate data. Since the primary benefit of using process-models compared to statistical models for projections of climatic suitability lies in the ability of process-models to incorporate physiological responses to a suite of altered environmental conditions, we contend the most informative application of process-models for this purpose should involve direct process-modeling of future climate variables.

It appears likely that the projections of bioclimate envelopes of the statistical model of Crookston et al. (2010) are overly pessimistic, and that additional work to integrate some physiological processes into the projection model is warranted to improve their predictive confidence. In particular, we believe there is a unique opportunity to bring in additional predictive power alongside the statistical Random Forests method by integrating regionally-relevant process-modeling such as the more generalized vegetation model MC2, species-level process models such as 3PG, or others.

Conclusions

Despite a variety of limitations and model assumptions across the modeling approaches considered, a general consensus across these datasets (including both statistical and process-based approaches) emerges highlighting several areas of near-term climatic vulnerability. In particular, the southwest Oregon coast is projected to lose habitat suitability for Western hemlock and Western redcedar and to become increasingly suitable for hardwoods and other species within the subtropical mixed forest vegetation type shown by the MC2 model. The Klamath Mountains and the southern extent of the Cascade Range are also projected to have broad losses of suitable climate for these species as the climate suitable for maritime evergreen needleleaf forests recedes up the Willamette Valley and becomes increasingly suitable for cool temperate cool mixed forests.

The only area that shows up relatively consistently as seeing increased climatic suitability for commercially important tree species appears to be for Douglas-fir in the northern and western edges of the BLM Lakeview District. However, it is important to keep in mind that climatic suitability is one of several factors that drive the potential for a species to be productive, and that soil conditions, disturbance regimes, or human land use, among other factors, may play a controlling role in limiting the ability for a species like Douglas-fir to be successfully grown in this area.

Given several very different modeling approaches consistently highlight similar regions of climatic vulnerability, it may reasonably be expected that these areas are likely to show the earliest impacts of a changing climate.

This review also confirmed the major differences in model sensitivities observed in other studies comparing statistical and process-based models. In particular, the Crookston et al. (2010) approach using Random Forests is observed to give much larger projections of contracting ranges for climatic suitability for several species than are found in the hybrid process-model of Coops et al. (2009, 2011). As the climatic suitability scores derived from this approach will feed directly into the Climate-FVS model, it is important to recognize at the outset of the growth-and-yield simulation that Climate-FVS is likely to mirror the negative forest impacts found with declining climatic suitability scores that come from the Random Forests approach.

Recognizing the inherent sensitivity of statistical models to a species' presence/absence in training data, we would encourage further research regarding the development of modeling approaches that accommodate a hybrid approach of process-models and statistical models. The example of Iverson (2011) offers great interest for further inquiry, as does further development and process-modeling of future climates beyond the scope of work by Coops and colleagues considered throughout this review. In general, we believe the statistical models such as Random Forests offer incredible predictive ability that can be significantly improved through refinements to the approaches of how FIA training data are used, as well as through the incorporation of process-model projections. Refinements to these bioclimate envelope projections could translate into improvements in the reliability of Climate-FVS, which uses these bioclimate envelope projections as direct inputs for growth-and-yield simulation (this process is described further below).

Finally, this report focuses on a modest segment of scientific research and datasets that can be used to inform climate-wise forest management planning. Although these models offer rich datasets with detailed projections of potential future climate scenarios, they should not be taken to inform management planning in isolation or without full recognition of the assumptions and uncertainties inherent in them. Consistent with the findings of Pearson and Dawson (2003), despite these caveats, we believe these models remain "a useful first approximation as to the potentially dramatic impacts of climate change on biodiversity." To complement these lines of evidence, we would encourage the use of a suite of other bodies of research and knowledge, including autecological and paleoecological research, and the expertise of local resource managers to inform the potential for individual species and ecosystems to adapt to novel conditions and define appropriate adaptation strategies.

How Climate-FVS uses suitability scores

As mentioned at the beginning of this report, the future projections of bioclimate envelopes reviewed here are intended to be used for a modeling study investigating the potential variability and uncertainty in achieving various forest management objectives for the BLM across the western Oregon Districts. This growth-and-yield modeling is planned with the use of the Climate-FVS model.

Climate-FVS incorporates changes in species suitability scores over the simulation period by modifying growth and mortality for each species within the FVS model. The source of these climate suitability scores is the Random Forests approach developed in Crookston et al. (2010) and reviewed in this report. Changes in climate suitability scores are factored into Climate-FVS calculations for Site Index, maximum Stand Density Index, and to define a range of climatic conditions that a localized variant of a species would tolerate (a proxy for genetic adaptability of a species variant). If a species' suitability score decreases over time, Climate-FVS will decrease the growth rate for that species; if the score decreases beneath a threshold of 0.5, Climate-FVS will start to increase the mortality rate for the species; and if the score decreases below 0.2, Climate-FVS will trigger local extirpation of that species. The 0.5 threshold to increase mortality rates corresponds to the observation that 99.5% of species presences observed in the FIA plots are in locations where climatic suitability was scored above 0.5. A more detailed description of the Climate-FVS program, including other climate-related factors that influence growth-and-yield projections, is available on the USFS website for FVS at http://www.fs.fed.us/fmsc/ftp/fvs/docs/gtr/ClimateFVS_UsersGuide.pdf.

Although the suitability scores are not the only drivers of growth and mortality within the growth-and-yield modeling process, it does appear likely that the model is likely to offer more pessimistic projections of climate change impacts on tree species than might be expected from mechanistic models. The recent addition of a new mortality factor (dClim) in version 2 of Climate-FVS that magnifies the effect of changing suitability scores appears likely to predispose the model to project even more severe mortality and declines in productivity. This factor is turned on by default, but can be changed or turned off by the user.

Based on the commonly reported observation of statistical models producing significantly more pessimistic projections of bioclimate envelopes, it appears likely that the use of these projections within Climate-FVS would be expected to produce more pessimistic projections of climate change impacts on forests compared to mechanistic growth-and-yield models, and that the additional mortality factor recently added is likely to exacerbate this difference.

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