

Natural areas as a basis for assessing ecosystem vulnerability to climate change

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Abstract. There are more than 580 natural areas in Oregon and Washington managed by 20 federal, state, local, and private agencies and organizations. This natural areas network is unparalleled in its representation of the diverse ecosystems found in the Pacific Northwest, and could prove useful for monitoring long-term ecological responses to climate change. Our objectives were to (1) evaluate potential effects of climate change on these natural areas and (2) develop strategies for selecting and prioritizing sites for long-term monitoring. Bioclimatic and Random Forest modeling were used to identify subsets of natural areas to prioritize for long-term monitoring efforts based on the current and projected (2020s, 2050s, 2080s) outputs from 13 future climate models. Projection consensus suggest some of the largest effects of climate change on natural areas may be the result of a substantial range increase in suitable climate for warmer-adapted forest types coupled with a reduction in habitat for cooler-adapted forest types. We identify four strategies that could be used for prioritizing sites and help manage and protect biodiversity in the Pacific Northwest, especially given uncertainty over climate change effects.

Key words: climate change; climate envelope; climate vulnerability; landscape monitoring; natural areas network; random forest.

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INTRODUCTION

Climate change is influencing global ecological dynamics, creating a need for robust monitoring systems that traverse geographic scales (IPCC 2013). Monitoring the impacts that climate change will have on ecological systems is important for several reasons. First, much of our understanding relies on modeled projections and hypotheses. Second, monitoring will allow us to anticipate and detect potential unpredicted effects. Finally, monitoring will aid managers in determining where early efforts to mitigate for change should best be focused geographically and at the ecosystem level. Therefore, it will be

important to test and validate these projections to ensure that our ability to predict is consistent with on-the-ground responses to climate change (Davis et al. 1998).

The ability to test and refine current climate change hypotheses and predictions requires programs that also span multiple spatial scales and ecological communities (Schellnhuber and Cramer 2006, Monitoring Team for Climate Change [MTCC] 2009, Haugo et al. 2015). In the United States and around the globe, there are several broadscale programs currently collecting data useful for studying climate change effects such as (1) National Centers for Environmental Information (NCEI 2016), (2) National Ecological Observatory

Network (NEON 2016), (3) LANDFIRE (2016), and (4) Biosphere Reserves (UNESCO 2016). These programs are improving our understanding of climate change effects, but limits exist to their scale, data inputs used, and focus (Brewer et al. 2004). For example, the U.S. Forest Service Forest Inventory and Analysis program (FIA) has systematically measured changes to forests across the United States since 1930 (USDA 2013). However, nonforested ecosystems are not included, and measurement plots are distributed every 2428 ha across forested land (Brewer et al. 2004, Manley et al. 2006, Millar et al. 2007). As a result, important fine-scale details about ecosystems may be missing, especially rare ecosystems which may also be particularly sensitive to climate change effects.

Natural areas sites could add depth and scale to current climate change monitoring programs and provide benchmarks for assessing change (Arcese and Sinclair 1997, Sinclair et al. 2002). These sites are formally designated to represent the diverse array of ecosystems found across the globe. They include representations of both common and rare ecosystems, protect threatened and endangered plants and wildlife, and serve as controls for experiments and reference sites for management activities (Franklin et al. 1972, Evenden et al. 2001, MTCC 2009, Wilson et al. 2009). In the Pacific Northwest, state heritage plans provide objective criteria for choosing natural areas (Washington Department of Natural Resources [WDNR] 2007, Oregon Natural Heritage Advisory Council [ONHAC] 2010). Minimal anthropogenic influences, wide distribution, and proportional representation across several ecological gradients suggest that natural areas may be ideal for monitoring long-term responses to climate change (Evenden et al. 2001, Jenkins and Bedford 1973, MTCC 2009; Wilson et al. 2009, Massie 2014).

There are >500 natural areas defined in Oregon and Washington (WDNR 2007, Wilson et al. 2009, ONHAC 2010). It is neither practical nor desirable to monitor all natural areas with equal intensity, especially if monitoring would require frequent on-site data collection. Therefore, the objective of this study was to develop a set of objective criteria for choosing a key subset of natural areas that could best inform science and management decisions associated with climate

change. First, we modeled potential effects of climate change on Pacific Northwest (PNW) natural areas. We developed two bioclimatic envelope models to correlate present vegetation and climate (Rehfeldt et al. 2006, 2012, Iverson et al. 2008, Siroky 2009, Mbogga et al. 2010, Biau 2012). We then used GIS to overlay a range of published climate projection models, future emission scenarios (from relatively mild to severe), and disturbance data (e.g., fire, insects, disease) onto natural areas (IPCC 2007; Wang et al. 2012a). Then, we developed a set of potential strategies for selecting and prioritizing natural areas for long-term monitoring based on our results.

MATERIALS AND METHODS

Study area

Our study area included 389 natural areas listed in Oregon's 2010 and Washington's 2007 and 2009 state heritage plans (Fig. 1; WDNR 2007, 2009, ONHAC 2010). We also included 39 proposed research natural areas (RNAs) listed in current U.S. Forest Service forest planning documents, and 92 Bureau of Land Management Areas of Critical Ecological Concern (ACECs) that may be included in future state heritage plan revisions (WDNR 2007, ONHAC 2010). The Pacific Northwest is characterized by 14 distinct level III ecoregions spanning from sea level to approximately 4390 m in elevation (Omernik and Griffith 2008). The Cascade Range (Cascades) runs north-south and creates a significant rain shadow effect, with west-side ecoregions influenced primarily by maritime climate and east-side ecoregions influenced by continental climate (Littell et al. 2009). West of the Cascades is characterized by mild temperatures with annual precipitation ranging from 75 cm (30 inches) to 250 cm (100 inches) in the Cascades, and up to 500 cm (200 inches) in the Olympic Peninsula. East of the Cascades is generally characterized as high desert, which includes greater sun exposure, higher temperature variability, and less annual precipitation than the west side. Precipitation levels range from approximately 50 cm (20 inches) to as little as 18 cm (7 inches; CIG 2012).

Climate envelope modeling

First, we constructed a standardized 800-m² grid over the PNW region using ArcMap10

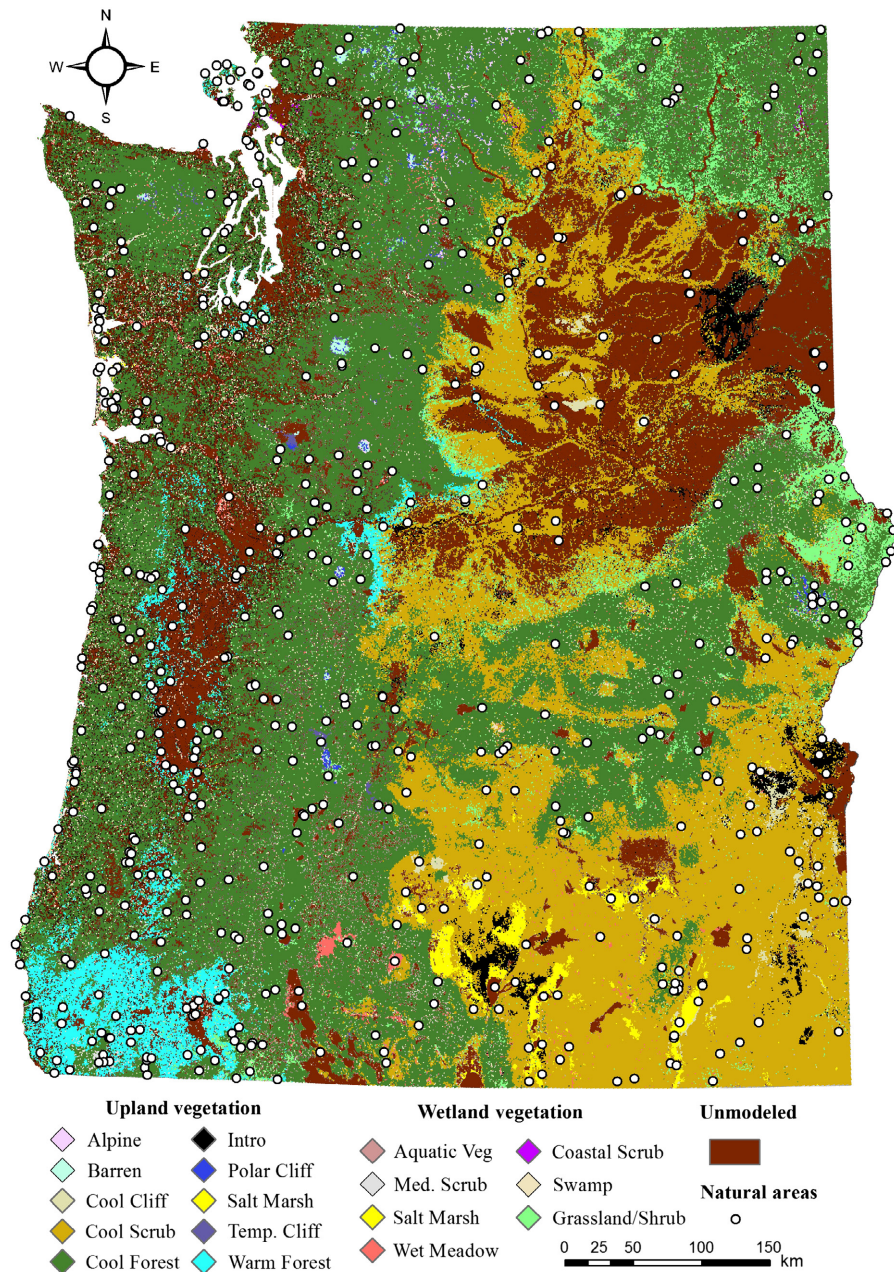


Fig. 1. Geographic Distribution of Oregon and Washington's Natural Areas. Alpine Scrub Forb Meadow and Grassland (Alpine), Barren (Barren), Cool Semidesert Cliff, Scree and Rock Vegetation (Cool Cliff), Cool Semidesert Scrub and Grassland (Cool Scrub), Cool Temperate Forest (Cool Forest), Introduced and Seminatural Vegetation (Intro), Polar and Alpine Cliff, Scree and Rock Vegetation (Polar Cliff), Salt Marsh (Salt Marsh), Temperate and Boreal Cliff, Scree and Rock Vegetation (Temp. Cliff), Warm Temperate Forest (Warm Forest), Marine and Estuarine Saltwater Aquatic Vegetation (Aquatic Veg), Mediterranean Scrub (Med. Scrub), Salt Marsh (Salt Marsh), Temperate and Boreal Freshwater Wet Meadow and Marsh (Wet Meadow), Temperate and Boreal Scrub and Herb Coastal Vegetation (Coastal Scrub), Temperate Flooded and Swamp Forest (Swamp), and Temperate Grassland, Meadow and Shrubland (Grassland/Shrub).

(ESRI 2011; Datum: North American, 1983, Projection: Albers). From this grid, we extracted centroid point values of latitude, longitude (decimal degrees), and elevation (30 m resolution) from the National Elevation Dataset (Gesch et al. 2002), which would later serve as our baseline input for the climate data program, ClimateWNA. Elevation was extracted at the centroid, rather than averaged over each 800-m² grid cell because ClimateWNA already includes bilinear interpolation and lapse-rate-based elevation adjustments to the specific input coordinates (Wang et al. 2012b). Second, vegetation formation class from the National Gap Analysis Program's (GAP 2011) vegetation mapping layer was assigned to each centroid coordinate. Formation class (hereafter, class) is the highest physiognomic level of the hierarchical National Vegetation Classification System (Grossman et al. 1998). Urban, developed, disturbed, aquatic, and classes with fewer than 60 cells were omitted from analyses (Rehfeldt et al. 2006, 2012, Iverson et al. 2008). The final data set included 509,816 points representing 16 classes over both forested and nonforested areas. Classes were then separated into "upland" and "wetland" vegetation to improve modeling accuracy (Table 1). Salt marsh class was included in both models as it can occur in wetland and nonwetland areas (USDA NRCS 2014). Static soil and topographic attributes (Integrated Landscape Assessment Project) were extracted to the grid cell centroid points to further improve model accuracy (Gaines et al. 2013). Finally, aspect was cosine-transformed to help standardize north-facing slopes (Roberts 1986).

Climate data

Climate data for the reference period, 1961–1990, and for three future periods 2011–2040 (2020s), 2041–2070 (2050s), and 2071–2100 (2080s) were generated using ClimateWNA (version 4.72). Baseline climate data outputted by ClimateWNA rely on downscaling 4-km (2.5 arc min) climate grids from PRISM (Daly et al. 1994, 2007, Wang 2006, Wang et al. 2012b). Thirteen climate projections were chosen to represent three emission scenarios (A2, A1B, and B1) applicable to PNW (Mote et al. 2005, Mote and Salathé 2009, Murdock and Spittlehouse 2011). Projections

were grouped by average predicted temperature increases—0.9°C (mild), 2.3°C (moderate), and 3.3°C (extreme; Table 2). Two hundred and thirteen climate variables (144 monthly, 48 seasonal, and 21 annual) were produced for reference climate values and future climate estimates based on latitude, longitude, and elevation.

Statistical procedures modeling relationships between climate and ecosystems

We used Random Forest (Breiman 2001, Liaw and Wiener 2002) within R (R Core Team 2013) to model the relationship between environmental variables (climate, soil, and topography) and vegetation formation class. All monthly, seasonal, and annual variables were included simultaneously in the model to improve model accuracy (Wang et al. 2012a). Model building started with relating predictor variables to a

Table 1. Point count from the systematic 800-m point grid across the PNW for each vegetation formation class in the upland (consecutive type code Alpine through Warm Forest) and wetland (consecutive type code Aquatic Veg through Grassland/Shrub) models.

Type code	Formation classes	Count
Alpine	Alpine Scrub, Forb Meadow and Grassland	799
Barren	Barren	804
Cool Cliff	Cool Semidesert Cliff, Scree and Rock Vegetation	4387
Cool Scrub	Cool Semidesert Scrub and Grassland	145,956
Cool Forest	Cool Temperate Forest	263,822
Intro	Introduced and Seminal Natural Vegetation	14,100
Polar Cliff	Polar and Alpine Cliff, Scree and Rock Vegetation	787
Salt Marsh	Salt Marsh	7389
Temp. Cliff	Temperate and Boreal Cliff, Scree and Rock Vegetation	1845
Warm Forest	Warm Temperate Forest	20,940
Aquatic Veg	Marine and Estuarine Saltwater Aquatic Vegetation	98
Med. Scrub	Mediterranean Scrub	429
Salt Marsh	Salt Marsh	7389
Wet Meadow	Temperate and Boreal Freshwater Wet Meadow and Marsh	4950
Coastal Scrub	Temperate and Boreal Scrub and Herb Coastal Vegetation	264
Swamp	Temperate Flooded and Swamp Forest	14,563
Grassland/Shrub	Temperate Grassland, Meadow and Shrubland	28,612

Table 2. The 13 climate models used for analyzing the range of change in climate suitability and grouped by prediction in temperature increase by the 2050s, and based on point grid averages.

Model	Emission scenarios	Run	Temp_chng	Precip_chng
Mild				
MRI-CGCM2.3.2	B1	5	0.83	0.06
ISS-AOM	A1B	1	0.95	-0.09
CSIRO-Mk3.0	B1	1	1.01	0.01
BCCR-BCM2.0	A2	1	1.51	0.04
Moderate				
GFDL-CM2.0	A2	1	2.08	-0.08
MPI-ECHAM5	A1B	3	2.15	0.05
MIROC3.2_medres	A2	2	2.12	-0.01
UKMO-HadCM3	B1	1	2.37	-0.03
Extreme				
CCCMA-CGCM3.1	A2	4	2.61	0.08
IPSL-CM4	A1B	2	2.84	0.15
NCAR-CCSM3	A1B	5	3.13	0.00
UKMO-HadGEM1	A1B	1	3.84	-0.03
MIROC3.2_Hires	B1	1	3.03	0.07

Notes: Temp_chng and precip_chng are the precipitation and temperature difference between current and predictions for the 2050s based on the grid point values. Temperature change is in Celsius. The mild grouping average temperature increase was 0.9°C, moderate grouping predicted increase of an average of 2.3°C, and extreme were the most extreme predictions with average temperature increases of 3.3°C.

random bootstrap sample of two-thirds of the observations. Observations were split into nodes based on a random selection of predictor variables until no further improvements could be made to each classification tree (Breiman 2001). This process was repeated to create a “forest” of classification trees. We assessed model accuracy using an “out-of-bag” (OOB) model prediction, which is based on internal cross-validation embedded within each Random Forest model (Breiman 2001, Liaw and Wiener 2002). An error matrix was created for the upland and wetland models that compared model predictions with reference values and kappa values (Cohen 1960).

Each model was built with 200 classification trees. The number of randomly selected predictor variables, *mtry*, was set at 12 based on *tuneRF*, which searches for an optimal value of selected predictor variables (Liaw and Wiener 2002). Models started with 214 initial predictor variables (all monthly, seasonal, and annual climate variables from ClimateWNA and elevation). Only predictors that degraded prediction accuracy when randomly permuted (variable

importance) or which contributed to a large decrease in impurity from parent to subsequent nodes (Gini importance) were retained in the modeling building process. We relied on both importance measures because of known limitations of each (Strobl et al. 2007). Final models contained 30 (upland) and 28 (wetland) predictor variables (Table 3).

Large differences in sample sizes resulted in poor accuracy for rare cover classes. Error was reduced using the *cutoff* parameter in Random Forest (Tables 4 and 5). Cutoff values were selected based on balancing highest prediction accuracy for individual classifications with highest accuracy for the overall model. Cutoff values reduced overall accuracy for the upland vegetation model by 0.39% but improved individual accuracy for the less dominant cover classes by an average of 7.2%. Cutoff values for the wetland vegetation model improved the overall modeling accuracy by 0.61%. There was a 1% reduction in individual accuracy of dominant cover types but an increase of >4% for less dominant cover types (Tables 4 and 5).

Effects of climate change

Estimated effects of future climate change were assessed by comparing current distribution of vegetation formation class between the two reference models and the 13 future projections for the 2020s, 2050s, and 2080s. First, regional and ecoregional losses, gains, and elevation shifts in vegetation formation classes were estimated based on average pixel counts for each formation class over all the models. Second, certainty in the future formation class was based on frequency of future model agreement (i.e., model consensus) over the three time periods (Heikkinen et al. 2006, Araujo and New 2007, Diniz et al. 2009, Marmion et al. 2009). If grid point classification for reference models was the same in the future, a score of 0 was given; if different, a score of 1. Majority (>6 models) consensus was used to identify regions where future formation class differed from the reference period. Additionally, for each point with predicted change, corresponding future classifications were aggregated to examine majority change consensus. Model consensus was used again when projections were separated into the three categories based on predicted temperature increases (mild, moderate, and extreme)

Table 3. Environmental variables included in the upland and wetland model (from a total of 213 variables).

Explanatory variable	Upland	Wetland
Elevation	X	X
Aspect (cosine-transformed)	X	
Slope	X	X
Depth	X	X
AWC (available water capacity)	X	X
BD (bedrock)	X	X
Sand	X	X
Silt	X	X
Clay	X	X
Rock	X	X
pH	X	
Hydr_index		X
Taxorder_index		X
AWC_100		X
BD_100		X
Tmin_at—Min Temperature (Autumn)	X	
PPT_wt—Precipitation (Winter)	X	
PPT_sm—Precipitation (Summer)	X	X
PAS_wt—Precipitation as snow (Winter)		X
Eref_sm—Hargreaves reference evaporation	X	
Eref_at—Hargreaves reference evaporation	X	
Tmax03—Max Mean Temperatures (March)		X
Tmax04—Max Mean Temperature (April)	X	X
Tmax12—Max Mean Temperature (December)	X	
Tmin02—Min Temperature (February)	X	
Tmin09—Min Temperature (September)	X	X
Tmin10—Min Temperature (October)	X	
PPT01—Precipitation (January)	X	
PPT06—Precipitation (June)		
DD5_04—Degree-days above 5°C (April)		X
DD5_06—Degree-days above 5°C (June)	X	
DD5_09—Degree-days above 5°C (September)		X
DD_18_04—Degree-days below 18°C (April)	X	
Eref11—Hargreaves reference evaporation (November)		X
TD—Temperature difference between MWMT and MCMT	X	X
MSP—Mean summer (May to September) precipitation (mm)	X	
SHM—Summer heat:moisture index (MWMT)/(MSP/1000)		X
DD_18—Degree-days below 18°C, heating degree-days		X
bFFP—The Julian date on which FFP begins	X	X
EMT—Extreme minimum temperature over 30 years	X	
EXT—Extreme maximum temperature over 30 years		X
CMD—Hargreaves climatic moisture deficit	X	

Note: Variable choices are based on the variable's importance for prediction accuracy or the variables that contributed to a large decrease in impurity from parent to subsequent nodes (Gini index).

to give a broader range of possible changes in climate suitability.

Natural area site selection

We identified natural areas as “vulnerable” if there was a majority consensus to a shift in climate suitability for the class the natural area was designated for and representing. The potential

vulnerability of natural areas to climate change was evaluated by intersecting natural area boundaries in ArcMap with the regionwide 800-m pixel grid for the 2020s, 2050s, and 2080s. Approximately 75% of the natural areas overlapped with probabilities of future formation class climatic suitability. Natural areas that did not intersect (usually due to small size) were

Table 4. Accuracy statistics for the upland vegetation model.

Obs†‡	Predicted†										Totals	% Cor
	AL	BA	CC	CS	CF	IN	PC	SM	TC	WF		
AL	599	2	0	13	172	0	3	0	3	7	799	75.0
BA	3	678	0	1	87	0	12	8	13	2	804	84.3
CC	0	0	2687	1238	147	274	0	32	5	4	4387	61.2
CS	3	0	894	131,596	8424	3459	1	1217	10	352	145,956	90.2
CF	82	35	88	10,704	246,720	356	29	81	134	5593	263,822	93.5
IN	0	0	328	6206	474	6874	0	188	1	29	14,100	48.8
PC	8	30	0	13	71	1	646	5	12	1	787	82.1
SM	1	3	28	1634	107	204	2	5397	1	12	7389	73.0
TC	8	7	11	46	478	7	8	1	1276	3	1845	69.2
WF	1	3	0	259	3869	9	0	1	0	16,798	20,940	80.2
Totals	705	758	4036	151,710	260,549	11,184	701	6930	1455	22,801		
% Cor	85.0	89.4	66.6	86.7	94.7	61.5	92.2	77.9	87.7	73.7		
RF	0.08	0.09	0.07	0.12	0.15	0.09	0.09	0.08	0.08	0.08		
Correct												89.7
Kappa												0.818

Notes: Bold text indicates number of correct point classifications. Row and column % correct are calculated by subtracting false negative and false positive rates. Total % correct is calculated by subtracting total model OOB error rate from one.

† AL = Alpine, BA = Barren, CC = Cool Cliff, CS = Cool Scrub, CF = Cool Forest, IN = Intro, PC = Polar Cliff, SM = Salt Marsh, TC = Temp Cliff, WF = Warm Forest, Total = Row Totals, % Cor = % Correct, Correct = Total % Correct.

‡ Obs = Observed, Totals = Column Totals, RF = Correct RF cutoff values.

omitted from further analyses ($n = 60$). Remaining natural areas were then classified based on model consensus, percentage of model agreement, and percentage of natural area.

Data from the Forest Health Protection (Forest Health Assessment [FHA]) aerial survey of forest insect, disease, and other disturbances and the Monitoring Trends of Burn Severity (MTBS) occurrence of fires >1000 acres were intersected with the natural areas using ArcMap. Vulnerable

natural areas were also identified based on disturbance occurrences and containing pixels with predicted change in climate suitability for their current formation class.

RESULTS

Climate envelope modeling

Accuracy measures were strong for both upland (OOB error rate: 10.34%; kappa: 0.818)

Table 5. Accuracy statistics for the wetland model.

Observed	Predicted							Row totals	% Correct
	Aquatic Veg	Med Scrub	Salt Marsh	Wet Meadow	Coastal Scrub	Swamp	Grassland/Shrub		
Aquatic Veg	75	0	6	3	0	14	0	98	76.50
Med Scrub	0	240	0	1	0	126	62	429	55.90
Salt Marsh	5	0	6922	165	2	134	161	7389	93.70
Wet Meadow	0	0	130	2974	8	1190	648	4950	60.10
Coastal Scrub	0	0	1	11	175	65	12	264	66.30
Swamp	1	92	101	745	39	11,808	1777	14,563	81.10
Grassland/Shrub	0	66	114	489	19	1639	26,285	28,612	91.90
Column Totals	81	398	7274	4388	243	14,976	28,945		
% Correct	92.6	60.3	95.2	67.8	72	78.8	90.8		
RF cutoff values	0.14	0.09	0.14	0.1	0.1	0.12	0.15		
Total % Correct									86.1
Kappa									0.785

Notes: Bold text indicates number of correct point classifications. Row and column % correct are calculated by subtracting false negative and false positive rates. Total % Correct is calculated by subtracting total model OOB error rate from one.

and wetland models (OOB error rate: 13.9%; kappa: 0.785) (error matrix shown in Tables 4 and 5). Topography, soil, monthly temperature, and seasonal precipitation were important prediction accuracy variables for both upland and wetland vegetation. The upland model included three seasons of variables (summer, autumn, and winter) and the wetland model included two (summer and winter; Table 3). Prediction accuracy was strongest for cool semi-desert scrub and grassland and cool temperate forest in the upland vegetation model (>90% for both); introduced seminatural vegetation (48.8%) was the least accurate. Prediction accuracy for the wetland vegetation model was highest for salt marsh and temperate grassland, meadow and shrubland (>92% correct), and lowest for Mediterranean scrub and temperate and boreal freshwater wet meadow and marsh (>51% correct). High accuracy for cool semidesert scrub and grassland, cool temperate forest, and temperate grassland, meadow and shrubland was a reflection of large land areas for each classification and the response to broad climatic patterns found in the region. Responses for seminatural vegetation, with the lowest accuracy of 48.8%, were harder to predict because its distribution is primarily dependent on anthropogenic influences change over time.

Our models predicted that 11.1% of the region would experience a shift in climate suitability for the current formation class by the 2020s and 20.2% by the 2050s and that 31.3% would change by the 2080s (Fig. 2a). Consensus for the 13 models was highest for the 2020s with complete model consensus for 72% of the area. However, by the 2080s, the area that showed complete model consensus dropped to 39% of the region (Fig. 2b–d). Relaxing model consensus to 12 of the 13 models resulted in agreement across 79% of the region for the 2020s and 52% of the region for the 2080s.

There were significant range shifts for several vegetation formation classes (Table 6). Greatest reduction for upland classes was predicted for class cool temperate forest with an approximately 108,000 ha predicted unsuitable by the 2080s. Alpine scrub, forb meadow and grassland, and polar and alpine cliff, scree and rock vegetation were predicted to have steady reductions of suitability during this same time period. In contrast, warm temperate forest was predicted to

increase an average of 80,000 ha and cool semi-desert scrub and grassland increased 19,000 ha of suitability over the modeled time period.

Increases in suitable climate for wetland formation classes were observed for temperate flooded and swamp forest and salt marsh classification with an average of 57,070 and 41,960 ha increase across the region from the 2020s through the 2080s (Table 6). Largest reductions were in temperate and boreal freshwater wet meadow and marsh and temperate grassland, meadow and shrubland, with an average decrease of 35,450 and 57,260 ha for the same time period.

Shifts in formation class were similar between ecoregions and the broader PNW region. The proportion of suitable climate for cool temperate forest decreased by >1000 ha by the 2080s for all ecoregions except the Canadian Rocky Mountain Ecoregion. Models predicted a decrease of <350 ha in climate suitability for cool temperate forest for this ecoregion. East and West Cascades, Klamath Mountains, and Puget Trough ecoregions were predicted to have the greatest increase (>4000 ha in each) in climate suitability for warm temperate forest. The largest increase for warm temperate forest was in the Coast Range ecoregion with an increase of >10,000 ha in suitability with a concurrent decrease of 10,000 ha for cool temperate forest type. General predictions for wetland formations were decreases in climate suitability for temperate grassland, meadow and shrubland, and increases in temperate flooded and swamp forest and salt marsh.

Movement of upland formation classes to higher elevations was predicted at the regional level. However, warm temperate forest and introduced seminatural vegetation also showed a shift toward lower elevations for the 2020s and 2050s (Table 7). Ecoregion-level assessment showed similar trends. The highest predicted upward movements of cool temperate forest class by the 2080s (>900 m) was predicted for Klamath Mountains and Northwest Coast ecoregions. Projections of downslope movement for wetland classes were observed for marine and estuarine saltwater aquatic vegetation, Mediterranean scrub temperate and boreal scrub and herb coastal vegetation, and temperate flooded and swamp forest. Ranges for salt marsh, temperate and boreal freshwater wet meadow and marsh, and temperate grassland, meadow and shrubland were projected to shift upward in elevation.

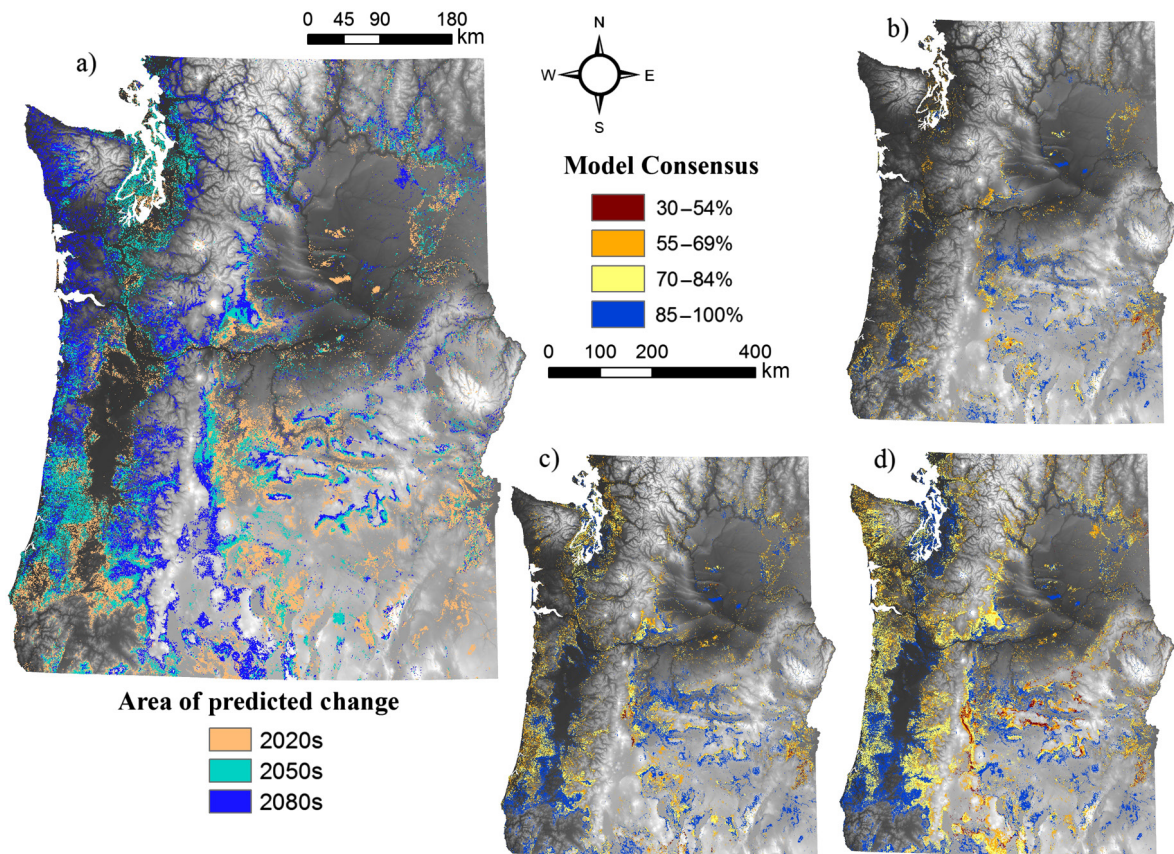


Fig. 2. Overall area of predicted change of vegetation formation class from the 2020s to the 2080s across the PNW, based on majority prediction from the 13 future projections resulting in a different formation class compared to the reference period (a) and consensus for the 13 climate models from the 2020s to the 2080s for the PNW, based on majority prediction from the 13 future projections resulting in a different formation class compared to the reference period and the percentage of agreement of the projections to what the formation class would be suitable (b–d). For all panels, grayscale background indicates elevation (light gray = high elevations).

Natural area site selection

The number of vulnerable natural areas (i.e., cells predicted to change in suitability from one vegetation formation class to another) went from 29 in the 2020s, 57 in the 2050s, and 68 in the 2080s based on 100% model consensus of all 13 models (Table 8). Every ecoregion had at least one vulnerable natural area based on 100% consensus except for the Okanogan and Snake River Plain ecoregions. The number of vulnerable natural areas increased from the 2020s to the 2080s except for the Blue Mountains, East Cascades, and West Cascades where the number increased in the 2050s but decreased in the 2080s. The Northern Basin and Range Ecoregion had six natural areas

with predicted change in the 2020s, increasing to nine by the 2080s. Vulnerable natural areas in the Coast Range and Klamath Mountains ecoregions more than tripled by the 2080s and doubled in the Blue Mountains and Puget Trough ecoregions. All ecoregions in the 100% model consensus analysis, except for the Columbia Plateau, Okanogan, and Snake River Plain ecoregions had at least one natural area with change predicted from the 2020s all the way through to the 2080s (18 in total). Separating models by future predicted temperature increase (mild, moderate, and extreme), relaxing model consensus (>50%), and analyzing consecutive time intervals (2020s, 2050s, and 2080s) resulted in the 137 natural areas for mild

Table 6. Regional percent cover change for the upland and wetland formation classes of the PNW, based on averaged pixel counts from the 13 climate model predictions comparing current to the 2020s through the 2080s.

Type code	Formation class	Current total % cover	Percentage change		
			2020s	2050s	2080s
Alpine	Alpine Scrub, Forb Meadow and Grassland	0.15	-0.08	-0.19	-0.26
Barren	Barren	0.16	-0.07	-0.07	0.02
Cool Cliff	Cool Semidesert Cliff, Scree and Rock Veg	0.88	-0.51	-0.62	-0.74
Cool Scrub	Cool Semidesert Scrub and Grassland	32.92	0.16	0.21	0.20
Cool Forest	Cool Temperate Forest	56.52	-0.17	-0.40	-0.65
Intro	Introduced and Seminal Vegetation	2.42	-0.04	0.71	1.68
Polar Cliff	Polar and Alpine Cliff, Scree and Rock Veg	0.15	-0.13	-0.18	-0.22
Salt Marsh	Salt Marsh	1.50	0.29	0.35	-0.04
Temp Cliff	Temperate and Boreal Cliff, Scree and Rock Veg	0.32	-0.11	-0.24	-0.34
Warm Forest	Warm Temperate Forest	4.95	0.95	2.84	5.45
Aquatic Veg	Marine and Estuarine Saltwater Aquatic Veg	0.14	-0.01	-0.01	-0.01
Med Scrub	Mediterranean Scrub	0.71	0.01	-0.11	-0.18
Salt Marsh	Salt Marsh	12.92	1.31	1.25	0.95
Wet Meadow	Temperate and Boreal Freshwater Wet Meadow and Marsh	7.79	-1.33	-0.66	-0.97
Coastal Scrub	Temperate and Boreal Scrub and Herb Coastal Veg	0.43	0.34	-0.02	-0.01
Swamp	Temperate Flooded and Swamp Forest	26.59	1.67	0.98	2.10
Grass/Shrub	Temperate Grassland, Meadow and Shrubland	51.42	-1.66	-1.24	-1.87

scenarios and 193 for extreme scenarios meeting the selection criteria.

Natural areas and qualitative risk assessment

There were >400 documented disturbances on natural areas over the past 30 years. This included

15 different beetle infestations by Douglas-fir beetle, fir engraver, western pine beetle, and mountain pine beetle in whitebark pine, lodgepole, ponderosa, sugar pine, and western white pine. Other disturbances included blister rust, Swiss needle cast, and unspecified hardwood

Table 7. Regional elevation change for the upland and wetland formation classes in the PNW, based on averaged pixel counts from the 13 climate model predictions comparing current to the 2020s through the 2080s.

Type code	Current average regional elevation (m)	Change in elevation from current		
		2020s	2050s	2080s
Alpine	2104	6	16	22
Barren	1618	57	62	180
Cool Cliff	794	15	-36	-85
Cool Scrub	939	-9	42	56
Cool Forest	897	50	124	217
Intro	1101	-125	-129	-94
Polar Cliff	2272	36	36	37
Salt Marsh	628	-29	-32	-24
Temp Cliff	1526	20	38	59
Warm Forest	509	-50	-33	47
Aquatic Veg	16	-13	-14	-14
Med Scrub	588	-235	-232	-245
Salt Marsh	535	-31	229	228
Wet Meadow	695	79	71	22
Coastal Scrub	548	-537	-537	-540
Swamp	676	-15	-12	-35
Grassland/Shrub	869	46	57	60

Table 8. Number of natural areas with 100% consensus of change from the 13 model projections for the 2020s, 2050s, and 2080s, sum of their hectares, and the percentage compared to total natural area, area for each ecoregion.

Ecoregion	2020s			2050s			2080s		
	No.	Sum of ha	% of total	No.	Sum of ha	% of total	No.	Sum of ha	% of total
Blue Mountains	3	256	0.31	11	832	1.00	8	640	0.77
Canadian Rocky Mountains	1	64	3.14	1	64	3.14	1	64	3.14
Coast Range	3	192	1.37	8	832	5.96	10	1152	8.25
Columbia Plateau	1	64	0.10	4	576	0.87	4	256	0.39
East Cascades	3	192	0.56	6	512	1.50	3	320	0.94
Klamath Mountains	2	128	0.83	6	768	4.97	10	1536	9.93
North Cascades	1	64	0.17	1	64	0.17	3	256	0.68
Northern Basin and Range	6	1472	0.56	7	2048	0.78	9	2240	0.86
Northwest Coast	2	128	0.82	4	448	2.87	6	1664	10.65
Okanogan			0.00			0.00			0.00
Puget Trough	4	576	5.63	6	896	8.77	8	896	8.77
Snake River Plain			0.00			0.00			0.00
West Cascades	2	128	0.43	1	64	0.21	3	256	0.85
Willamette Valley	1	64	2.18	2	128	4.35	3	320	10.88

decline. There were 148 documented fire occurrences in 84 natural areas since 1984. The number of vulnerable natural areas based on >50% model consensus to have a shift in climate suitability and experienced natural disturbance(s) increased from 184 in the 2020s to 273 in the 2080s (Table 9). Within the last 30 years, 52 natural areas specifically had fire disturbances, with 25 of those also displaying evidence of other forest disturbances such as western and mountain pine beetle and various needle cast diseases.

DISCUSSION

Our climate vulnerability assessment of PNW natural areas and approach for selecting a subset of natural areas for long-term monitoring is unique in two distinct ways. First, we applied bioclimatic envelope models to both forested and nonforested lands as a means to select ecosystems for long-term study of climate change. Prior modeling efforts in the PNW linking climate variables and vegetation distribution were concentrated on forest landscapes (MTCC 2009), with heavy reliance on FIA data (Reams and VanDeusen 1999, Brohman and Bryant 2005). Second, while there is currently limited information and a critical need for quantifying the relationships between forest disturbance (e.g., fire, insect, and disease) and climate change (Bentz

et al. 2010, Kliejunas 2011, Sturrock et al. 2011, Weed et al. 2013), coupling disturbance with climate modeling provides a platform for site selection that accounts for increased ecosystem vulnerability based on ecological thresholds of change among multiple stressors (Pearson and Dawson 2003, Brook et al. 2009, Rehfeldt et al. 2012).

Our models generally suggest reduced area of climate suitability for cool temperate forest types and an increase in area for warm temperate forest and scrub and grassland types (see Table 6). This overall regional shift to generally drier ecosystems is consistent with other studies projecting effects of climate change on ecological communities in the PNW region (Hamann and Wang 2006, Rehfeldt et al. 2012, Wang et al. 2012a). These parallel findings, coupled with data suggesting PNW natural areas are representative of the ecosystems across PNW (Massie 2014), provide support that monitoring a subset of natural areas is one way to direct monitoring efforts and resources to a smaller, but representative portion of the whole PNW natural landscape.

Currently, cool temperate forest is the most extensive formation class designation in the PNW. The natural areas network is representative of the current distribution of cool temperate forest (Massie 2014). However, the large spatial extent of this classification may indicate a need to add

Table 9. Number of natural areas with recorded disturbance occurrences from the MTBS or FHA, >50% consensus of change from the 13 model projections for the 2020s, 2050s, and 2080s, sum of their hectares, and the percentage compared to total natural area, area for each ecoregion.

Ecoregion	2020s			2050s			2080s		
	No.	Sum of ha	% of total	No.	Sum of ha	% of total	No.	Sum of ha	% of total
Blue Mountains	35	16,128	19.30	38	21,760	26.05	40	24,704	29.57
Canadian Rocky Mountains	1	64	3.14	1	64	3.14	1	64	3.14
Coast Range	15	1664	11.91	22	4096	29.33	28	7488	53.61
Columbia Plateau	14	9472	14.25	15	10,048	15.12	18	10,624	15.98
East Cascades	10	3584	10.51	16	4992	14.64	21	8128	23.84
Klamath Mountains	23	4032	26.07	24	5184	33.52	27	6080	39.31
North Cascades	5	896	2.36	8	1216	3.21	8	2432	6.41
Northern Basin and Range	37	48,640	18.59	37	57,216	21.87	39	57,472	21.97
Northwest Coast	6	1664	10.65	13	3072	19.67	19	7360	47.12
Okanogan	3	448	2.48	4	512	2.84	4	320	1.77
Puget Trough	13	1536	15.03	18	3072	30.05	18	3072	30.05
Snake River Plain	3	2048	39.79	3	2496	48.50	3	2368	46.01
West Cascades	13	1856	6.18	23	5184	17.26	35	11,584	38.56
Willamette Valley	6	704	23.95	12	1216	41.36	12	1344	45.72

additional natural areas within this class. From our models, natural areas in the Coast Range and Puget Trough ecoregions are projected to exhibit the most dramatic shifts in suitability from cool temperate to warm temperate forest (Fig. 2 and Table 8). Average temperature in the Puget Trough has increased 1.3°C (2.3°F) since 1900, which is a faster rate than average global trends (Snover et al. 2005). Concurrent reduction in regional suitability for the higher elevation alpine and polar formation class types is also consistent with other studies (Rehfeldt et al. 2012, Wang et al. 2012a). The alpine and polar formation classes are currently rare in PNW and may be especially vulnerable to extirpation if temperature trends continue on current trajectories.

Wetland formation classes were less likely to change from one class to another compared to upland vegetation classes. This may be because many wetland plants are adapted to site-specific topography, geomorphology, hydrologic regimes, and nutrient cycling (Christy and Alverson 2011). Exceptions include generalists such as *Atriplex* spp. that have physiologic characteristics (e.g., C-4 photosynthesis) that allow for adaptation to arid conditions (Edwards and Walker 1983, Ehleringer et al. 1997, Howard 2003).

Our analysis suggests several potential strategies for selecting and prioritizing established natural areas for long-term monitoring of climate

change. One approach would be to select sites where the predictions from all 13 climate models project a consistent shift in climate suitability to a new class (e.g., consensus mapping). For example, from the 2020s to 2080s, the Coast Range, West Cascades, and East Cascades ecoregions have the largest amount of land area in which all 13 models project shifts from cool temperate forest to either warm temperate forest or cool semi-desert scrub-grassland (see Table 8). While these three ecoregions are predominately forested, monitoring efforts that focus on the transitional zones within the cool temperate forest classification and interior areas of cool temperate forest distribution would provide an opportunity to compare effects of climate change between robust, core areas vs. transitional edges of this vegetation class distribution.

There also is opportunity to integrate site selection for ecoregions in areas where model consensus suggests no predicted shift in climate suitability. For example, natural areas in the Canadian Rocky Mountains and North Cascades ecoregions have minimal area of predicted shifts in suitability (Table 8). Monitoring in these regions may help identify variables that might drive vegetation change in various other locations (Wang et al. 2012a). If future changes are observed in areas where no predicted shift in vegetation suitability existed, additional examination of such areas provides opportunity to identify climate

change factors that drive change, but are not yet be accounted for in current models.

A second site selection strategy would be to concentrate monitoring based on high model consensus for climate suitability shift, but low model consensus on future formation class. Such output is evident in the Blue Mountains, Klamath Mountains, and Puget Trough ecoregions (Fig. 2b–d). For example, current wetland formation classes such as temperate flooded swamp forest and temperate and boreal freshwater wet meadow and marsh have mixed results from climate models in terms of projected shifting climate suitability to salt marsh, Mediterranean scrub, or temperate grassland, meadow and shrubland. Relying less on the agreement of future change predictions, as with the first strategy, and selecting areas where there are multiple possible shifts in future climate suitability, increases the number of selected natural areas from 59 to 172. This difference provides opportunity to study a range of ecosystems from the alpine forests of the North Cascades to the arid lands of the Northern Basin and Range. However, a strategy focused on vegetation classes with reduced model agreement may require greater flexibility to shift monitoring efforts and location to account for future unpredictability (Wang et al. 2012a).

A third selection strategy would be to group and compare future temperature increases (e.g., mild, moderate, extreme; Kang and Yoo 2006) and model consensus within the mild, moderate, and extreme temperature groupings. Quantifying change based on model consensus from grouped predictions would provide thresholds for vulnerability based on projected temperature. Sites with predicted shifts in suitability based on mild future projections could be considered highest priority. Using grouped predictions would broaden the scope of ecosystem types and would increase monitoring sites in the coastal areas of the Puget Trough ecoregion and the ecological distinct Klamath Mountains ecoregion compared to using sites based on model consensus with the full set (13) of predictions. However, using grouped projections with similar thresholds of temperature change for site selection could omit areas of high vulnerability if future precipitation and temperature trajectories differ.

Finally, site selection could be based on combining climate modeling projections with recent

disturbance. Integrating disturbance data with climate projections provides a unique opportunity to assess ecosystem vulnerability based on multiple stressors. For example, multiple natural areas could be selected within each ecoregion by merging climate projections in areas with historic trends of insect or fire disturbance (with exception to the Canadian Rocky Mountains; see Table 9). Selection using this strategy could be further refined to only include areas where there is evidence of multiple disturbance agents. This would eliminate many sites from Washington, but would preserve broad coverage across ecoregions in Oregon. Using disturbance with climate projections could provide better insight into organism tolerance or adaption to changing conditions, compared to using only climate projections (Walther et al. 2002, Rehfeldt et al. 2006, Scholze et al. 2006, Glick et al. 2011).

We have highlighted various selection strategies that can be used to design an array of sites for monitoring effects of future climate change across the PNW. We recognize limitations exist to our methods, particularly those inherent in using modeled data from various sources (i.e., satellite data, ground plots, and aerial surveys). Such limitations are that (1) broadscale climate projections and modeling techniques do not incorporate localized and fine-scale processes, which could influence species distribution (Wang et al. 2012a), and (2) aerial detection surveys for disturbance are meant to only provide a baseline indicator of ecosystem disturbance rather than fine-scale accuracy (Johnson and Ross 2008). However, disturbance and ecosystem vulnerability may be the best approach for monitoring landscapes for climate effects across a range of ecological scales until additional methods are available for better incorporating fine-scale processes across large landscapes and ecosystem types (Noss 1999, Brohman and Bryant 2005).

This study represents one step toward developing a more comprehensive climate monitoring strategy for all lands and ecosystems and provides a unique approach to evaluate ecosystem response to ecological stress. Using the network to collect baseline data can not only be used to monitor changes to structural and biological heterogeneity, but can also be used to measure and compare resilience of natural areas to that of human influenced ecosystems. Additionally,

natural areas provide the opportunity for managers to better understand ecosystems capabilities and inabilities to adapt to changes across diverse ecosystems. Dependent on management goals and objectives, site selection could incorporate the following: (1) specific biotic and abiotic characteristics such as soil type and finer scaled species composition, (2) potential barriers and limitations to species movement, and (3) landscape context, including relationships with adjacent ecosystems and how climate may impact those relationships over time.

Further efforts to develop a comprehensive monitoring strategy should focus on the following: (1) coordination among agencies within the natural areas network to select sites based on the data generated from this study; (2) developing standardized protocols that can be used by all agencies across the natural areas network for measuring climate change-relevant variables; (3) collecting data to improve climate envelope model and prediction accuracy; and (4) periodically reassessing the vulnerability of natural areas as new information and knowledge become available. Overall, enhancing the monitoring program for the natural areas network will not only benefit the conservation of regional biodiversity within PNW, but may help lead to improved management options in the face of uncertainty over climate change effects. The natural areas network appears sufficiently robust to serve as a strong platform for examining long-term environmental change across PNW. Establishment of a climate change monitoring program based on natural areas using the approach demonstrated here will provide data to better understand the effects that climate change may have across all ecosystems found in this region.

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