esa ECOSPHERE

Projected range shifting by montane mammals under climate change: implications for Cascadia's National Parks

Kevin M. Johnston,[1] Kathryn A. Freund,[2] and Oswald J. Schmitz†

School of Forestry and Environmental Studies, Yale University, 370 Prospect Street, New Haven, Connecticut 06511 USA

Citation: Johnston, K. M., K. A. Freund, and O. J. Schmitz. 2012. Projected range shifting by montane mammals under climate change: implications for Cascadia's National Parks. Ecosphere 3(11):97. http://dx.doi.org/10.1890/ES12-00077.1

Abstract. We examined potential impacts of climate change over the next century on eight mammal species of conservation concern in western Washington State, under four warming scenarios. Using two species distribution models, including a logistic regression-based model and the "maximum entropy" (MaxEnt) model, we predicted the location and extent of the potential current and future range of each species based on a suite of environmental and geographical variables. Both models projected significant losses in range size within the focal area over the next century across all warming scenarios. Projections suggest that future ranges of high elevation species are likely to shrink inward and upward rather than shifting into new areas, and the average range elevation of most species is projected to increase significantly over time. Future projections for higher elevation species largely agreed across species distribution models, global climate model data, and carbon emission scenarios, although projections for lower elevation species were less consistent. The high elevation of the major national parks in this region is likely to aid in their ability to continue to support these species, and they are predicted to continue to act as important protected refuges, even while species' ranges may shrink dramatically elsewhere.

Key words: Cascadia; climate change; logistic regression model; MaxEnt model; range shifting; species distribution model; Washington State.

Received 14 March 2012; revised 6 September 2012; accepted 21 September 2012; **published** 7 November 2012. Corresponding Editor: M. Anand.

[1] Present address: Environmental System Research Institute, Redlands, California 92373-8100 USA.

[2] Present address: U.S. Department of Interior, Fish and Wildlife Service, Arlington, Virginia 22203 USA.

† **E-mail:** oswald.schmitz@yale.edu

Introduction

Climate change is altering the structure and functioning of communities and ecosystems by causing massive poleward and elevational shifts in the geographic range distributions of numerous plants and animals (Lovejoy and Hannah 2006, Malcolm et al. 2006, Parmesan 2006, Barnosky 2009, Walther 2010). These changes may jeopardize existing conservation efforts because parks and protected areas—the dominant strategy for biodiversity conservation—will have difficulty to meet their mandate to conserve communities of species that currently exist within their fixed jurisdictional boundaries (Peters and Darling 1985, Burns et al. 2003, Araújo et al. 2004, Hannah et al. 2007, Baron et al. 2009). Conservation must now deal with the inevitable fact that parks and protected areas may harbor new combinations of species and hence associated new community and ecosystem types and functioning (Burns et al. 2003, Baron et al. 2009, Lawler et al. 2010). This has accordingly precipitated calls for adapting conservation and management activities in ways that anticipate and respond to climate change. But, confronting and strategically responding to change will require knowing the number and kinds of species undergoing range shifts and the spatial extent of range shifting; information that is currently lacking for many parks and protected areas networks (Burns et al. 2003, Araújo et al. 2004, Hannah et al. 2007, Baron et al. 2009).

We addressed this uncertainty by conducting an analysis of potential range loss and range shifting of montane mammal species within the broader mountainous Cascadia region of the US Pacific Northwest and assessing whether these species will be retained over the next century within the three national parks—Olympic, Mount Rainier and North Cascades—that are nested within this region. It is hypothesized that montane species are especially vulnerable to climate change because they have limited geographic range sizes to begin with, they tend to be geographically isolated, and they have unique adaptations to montane environmental conditions (Theurillat and Guisan, 2001, Moritz et al. 2008, Barnosky 2009, LaSorte and Jetz 2010). We used species distribution modeling to address this hypothesis by relating data on species' geographic locations to environmental data or other predictor variables (Guisan and Thuiller 2005). Our study focused on eight mammal species (American marten (*Martes americana*), American pika (*Ochotona princeps*), Canada lynx (*Lynx canadensis*), elk (*Cervus canadensis*) gray squirrel (*Sciurus griseus*), hoary marmot (*Marmota caligata*), mountain goat (*Oreamnos americanus*), and wolverine (*Gulo gulo*)), under a variety of climate change scenarios. These species are high conservation priority mammal species based on the Washington Department of Fish and Wildlife Priority Habitats and Species List (WDFW 2008).

Methods

The focal area for analysis was the western three-quarters of Washington State (45.542° to 49.004° latitude and 124.737° to 118.762° longitude, see Fig. 1). This topographically complex landscape encompasses the three national parks and varying types of human-built environment surrounding them including managed forests, refuges, state, and private lands. The vegetation across the western half of the focal area is primarily maritime evergreen forest, while the southeastern section is dominated by temperate shrubland. The Cascade Range divides the study area from north to south, and is characterized by a mix temperate evergreen forest, subalpine fir, and tundra at increasingly higher elevations (Rogers 2009). Climate change is predicted to have varied effects in this region, including decreasing snow pack and extent of glaciers; disappearing alpine habitats; drying wetlands and soils; and changing precipitation patterns (Elsner 2009).

Overall modeling approach

Our goal was to develop, through the use of species distribution modeling, a sense of plausible future scenarios that, with expert opinion, could assist in devising conservation planning to support species conservation under changing climate. Modeling climate effects on species distributions requires the sequential use of different kinds of models, (e.g., models of future emissions of greenhouse gases, models of how global atmosphere respond to these emissions, models to downscale global climate projections to smaller spatial extents, models of the species' responses to climate change) that each carries uncertainties. We therefore ran multiple scenarios to cover the range of uncertainty in the different models.

Data sets

Variables that were included in the species distribution modeling were chosen because they were considered by the Washington State GAP program to be biologically important and meaningful for the focal species. Elevation data (variable "elevation") at approximately 30 meters were obtained from the United States Geological Survey National Map (USGS National Map Seamless Server 2009), and were also used to create slope ("slope") and aspect ("aspect") rasters using the ArcMap version 9.3.1. Data on current city limits and road networks were obtained from the Washington State Department of Transportation GeoData Distribution Catalog (WSDOT 2010) and were used to create "distance to roads" ("disthigh") and "distance to cities" ("distcity") rasters. In addition, climatic and ecological variables were obtained from the MAPSS-CENTURY 1 (MC1) dynamic general vegetation model, from Oregon State University

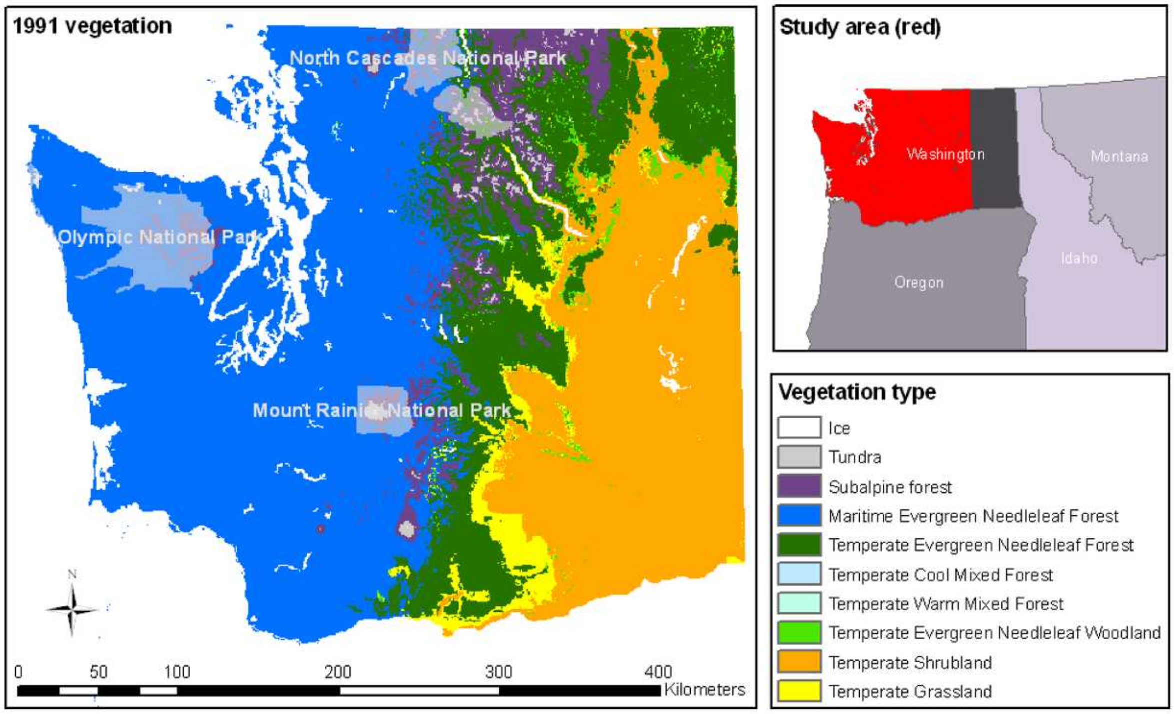


Fig. 1. Study area and vegetation types for contemporary (1991) scenario, from (MC1) dynamic general vegetation model. Major national parks present in this study are also shown.

(Bachelet et al. 2001, Rogers 2009, Rogers et al. 2011). This data source provided the climate variables precipitation ("ppt1991"), and mean annual temperature ("tmp1991"), as well as a categorical variable describing vegetation type ("veg") (e.g., see Fig. 1) at a grain size of 800 meters.

Data for the mammal species' current ranges were obtained from the Washington State Gap Analysis Project (Johnson and Cassidy 1997). Both "core" and "peripheral" habitat was mapped for each species, at an approximately 100-hectare grain size. All species were found in at least one of the national parks analyzed here (NPSpecies 2009). The average elevation of the current range ("range elevation") of each species is presented in Table 1.

Future climate and ecological data (all provided by the Oregon State MC1 model) were based on two widely used general circulation models (GCMs), including the high-sensitivity MIROC 3.2 medres ("Miroc"; Hasumi and Emori 2004) and the intermediate-sensitivity Hadley CM 3 ("Hadley"; Johns et al. 2003) models. Projections were compiled from each GCM using two different carbon dioxide emission scenarios prepared by the Intergovernmental Panel on Climate Change (IPCC), each with different assumptions for future greenhouse gas pollution, land-use and other driving forces that predict different degrees of reliance on carbon-based or fossil fuel energy. Scenarios included the A1B (mid-level, relying on "balanced" energy sources in an "integrated" world) and A2 (high-level, based on an increasingly populated and "divided" world) emission scenarios (IPCC 2000). These scenarios capture the more likely trends in future emissions growth: the increasingly unlikely B1/B2 (lower level) scenarios were not considered here.

All data were analyzed in ArcGIS/ArcInfo version 9.3.1 (ESRI 2009). Raster files were created and projected in the NAD 1983 State Plane Coordinate System for Washington (South). The climate data was the coarsest of the datasets at an approximately 800 meter grain size, and thus each cell in the climate data was approximately 0.65 square kilometers or 65

Table 1. Mammal species of conservation concern included in analysis; approximate average range elevation within study area is provided.

Common name	Scientific name	Family	National Park	Elevation (m)
Hoary marmot	*Marmota caligata*	Sciuridae	MR, NC, ONP†	1580
Canada lynx	*Lynx canadensis*	Felidae	MR,† NC	1565
Wolverine	*Gulo gulo*	Mustelidae	MR, NC	1295
Mountain goat	*Oreamnos americanus*	Bovidae	MR, NC, ONP	1175
American pika	*Ochotona princeps*	Ochotonidae	MR, NC	1140
American marten	*Martes americana*	Mustelidae	MR, NC, ONP‡	940
Western gray squirrel	*Sciurus griseus*	Sciuridae	NC	800
Elk	*Cervus elaphus*	Cervidae	MR, NC, ONP	765

Note: National Park abbreviations are as follows: Mount Rainier (MR), North Cascades (NC), Olympic National Park (ONP). The double dagger symbol ("‡") indicates that the National Park Service Species Database does not list the species as present, but the Gap Analysis range data overlaps the park boundaries. The dagger symbol ("†") indicates the reverse.

hectares in size. We treated both core and peripheral habitat equally as presence areas. Outside the species distribution we considered as absence.

We analyzed five-year running averages (modes) for the years 2020–2024 (early century), 2050–2054 (mid-century) and 2095–2099 (late-century), to provide three snapshots of potential range shifts throughout the 21st century for each of the four warming scenarios. Focusing on two GCMs and two emission scenarios gave us a total of four "warming scenarios" that capture a range of uncertainty in climate sensitivity and emission levels. We used two common species distributions modeling approaches: regression-based and maximum entropy species distribution models (Guisan and Zimmerman 2000) that differ in assumptions about species detectability (presence/absence in regression vs. presence only in maximum entropy). Our rationale for using both modeling approaches is that a higher level of confidence can be attributed to those areas where all the models agree and additional analysis should occur where they disagree. The climate model outputs in combination with the species distribution modeling resulted in 13 projections (one "contemporary" and 12 future) for each species per species distribution modeling approach, or 26 projections per species in total.

Regression-based presence/absence modeling

We used logistic regression to predict the probability that each mammal species was present at each geographical location (or cell) based on environmental variables. This technique has been used widely to predict the occurrence and habitat use of sensitive and at-risk species (Pearce and Ferrier 2000), and has been applied to analyses of climate change on wildlife (e.g., Johnston and Schmitz 1997, Burns et al. 2003). Logistic regression is applicable for our purposes because, unlike many data sets where true absences are uncertain, the GAP distributions used in this study meets this presence/absence requirement well.

Logistic regression as a general linear model (GLM) is a parametric approach that requires independent observations. Both the dependent and independent variables used in our study originate from GIS raster data and thus tend to be spatially autocorrelated, causing us to violate the requirement for independent observations if we used the full set of rasters in our analyses. We therefore constructed a GIS layer of random sample points distributed within the study area boundary. To avoid pseudoreplicaton, no two sample-points were within the distance of the diagonal of cells within the rasters. The values of the dependent and independent variables at the sample point locations (derived from the corresponding raster) were assigned to the point locations. There are alternative statistical approaches such as general linear mixed model (GLMM) or general least squares (GLS) approaches that could allow us to address autocorrelation explicitly. But, we implemented GLM because of the need to compare results with the alternative presence-only maximum entropy modeling that also does not address spatial autocorrelation in its calculations. We wanted to implement two models that address spatial autocorrelation in the same way so that comparisons of output were not confounded by differences due to treatment of autocorrelation.

We created the base model by running logistic regression on the 1991 GAP data that represented the "current" or baseline time period. For each species, the values for the dependent and independent variables were extracted from each 1991 raster and were associated to each sample point. Using a custom tool created within ArcGIS, the sample points were imported into the companion R logistic regression statistical program.

We ran scenarios with all variables (the independent variables) that are known to be biologically significant to each species. These included vegetation types, average yearly precipitation, average yearly temperature, elevation, slope, aspect, distance from cities, and distance from road. The identified variables that gave significant model fits and their fitted coefficients are presented for each species in Appendix A. We then explored whether or not including just those variables that were significant at $P < 0.1$ and $P < 0.05$ gave better model fits. Pilot analyses revealed that generally the AIC for models with fewer variables provided as good or poorer fit than models that included all of the significant predictor variables. Given that we were comparing two modeling approaches for consistency, we took the position that all the identified significant independent variables contribute something to the model fits (whether they met the $P < 0.1$ or 0.05 criterion or not) and thus kept all of the variables in the model.

Using the general logistic equation, multiplying each cell for each independent variable by the appropriate coefficient creates an ArcGIS Spatial Analyst Map Algebra statement. The product of each independent variable is added (using the general logistic equation) to create a probability surface identifying the likelihood of finding the species at each cell location given current conditions. All cell locations with a probability of 50% (0.5) or greater were selected to identify the potential distribution for the species. We selected 0.5 or 50% as the threshold value for creating distribution surfaces from the resulting probability surfaces. It may be possible to obtain a closer predicted distribution surface relative to the actual current distribution by varying the probability threshold because generally as the area covered by a species increases (more than 50%), the higher the optimum threshold value (greater than 0.5). Alternatively, generally if the area covered by the species is less than 50% of the study area, then a threshold value less than 0.5 will produce a range distribution closer to the actual. However, there were exceptions to both cases. The actual distribution provided a priori information about the species distribution, about the statistical population for the species. Since, we did not have knowledge of the distribution or the area the species would cover in the future, we could not assume that the future population will have the same a priori information about the existing distribution. So, conservatively, the only threshold that can be applied to future predictions with any level of confidence is 0.5 or 50% probability. We then used the same coefficients to project future distributions using biophysical landscape data from the climate change models for year 2015, 2050, and 2100. This process is repeated for each species.

Maximum entropy presence-only modeling

We prepared the Gap Analysis mammal range rasters for use in presence-only modeling by creating a randomly generated set of points across the study area and overlaid it with each range to produce presence points for each species. We then used the maximum entropy model MaxEnt to project future distributions. MaxEnt performs well in comparison with other distribution models, and it seems to be emerging as one of the most well-performing and easiest to use distribution models currently in practice (Elith et al. 2006).

For each species, we first ran MaxEnt Version 3.3.2 using all ten environmental variables under the current (1991) conditions. For each model run, MaxEnt automatically selected the best-fit combination of variables, and created a distribution map showing the probability of presence of a species at each cell under present conditions. Model performance was evaluated by dividing the presence points into random training (90%) and test (10%) datasets, and by analyzing the sensitivity and specificity across all thresholds (AUC score). We then used the

Table 2. Sensitivity, specificity, accuracy for the logistic regression and MaxEnt models for predicted current species distributions.

Species	Logistic regression model			MaxEnt model		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
Hoary marmot	0.659	0.970	0.936	0.623	0.982	0.942
Canada lynx	0.615	0.986	0.959	0.620	0.991	0.964
Wolverine	0.835	0.937	0.909	0.724	0.967	0.900
American pika	0.709	0.910	0.848	0.593	0.947	0.836
Mountain goat	0.750	0.931	0.880	0.695	0.967	0.889
American marten	0.786	0.879	0.842	0.668	0.960	0.845
W. gray squirrel	0.171	0.992	0.936	0.586	0.950	0.925
Elk	0.822	0.874	0.846	0.658	0.975	0.800

same (best-fit) model to predict future distributions for each species under each climate change scenario. Again, we defined a threshold of 0.5 (at least 50% probability of presence) as the cut-off for predicting the presence of a species.

Reliability of species distribution models

We evaluated the reliability of the model approaches by comparing model projections under current (1991) environmental conditions with our "known" species range data from the same year. Building on existing approaches (Fielding and Bell 1997) we evaluated model performances for each species by calculating the sensitivity and specificity of each model prediction (at a 0.5 threshold) in relation to the original distribution (Table 2) using the following equations:

$$\text{sensitivity} = \frac{\text{true positives}}{\text{true positives } + \text{ false negatives}}$$

$$\text{specificity} = \frac{\text{true negatives}}{\text{truenegatives} + \text{false positives}}$$

$$\text{accuracy} = \frac{\text{true positives} + \text{true negatives}}{\text{true positives} + \text{false positives} + \text{true negatives} + \text{false negatives}}.$$

We also calculated a measure of accuracy based on a combination of these metrics (Pearce and Ferrier 2000), and compared the total size of the original and predicted ranges under each model.

Projecting future distributions

We calculated the total area of the projected future range within our focal area under each warming scenario. We then determined the percent decline (or increase) in area in relation to the original (Gap Analysis) species range for each of the three snapshot periods (2020–2024, 2050–2054, 2095–2099). We also calculated the percentage change in elevation within each snapshot period. We conducted simple linear regressions using the original range size or elevation and the corresponding estimates for snapshot periods to examine changes in species range size and elevation over time. The rationale for this analysis was to test whether there was a projected decreasing or increasing trend in range size or elevation over time. We ran regressions across both models and separately for each model, and tested for differences between model projections using a pooled *t*-test.

Results

Maps comparing current (1991) observed and predicted distributions for all mammal species examined in our study are provided in Appendix B. We present in Fig. 2 for illustrative purposes the distribution of the wolverine from the original Gap Analysis data and the current distribution as projected by the logistic regression model and the MaxEnt model. Both models tended to show similar sensitivity, specificity, and accuracy for each species (Table 2). Accuracy was highest for both models for the hoary marmot and Canada lynx, and lowest for the American pika, American marten, and elk. Sensitivity was lower than specificity in most cases for both models, which suggests the models may be slightly underestimating current species presence at a proba-

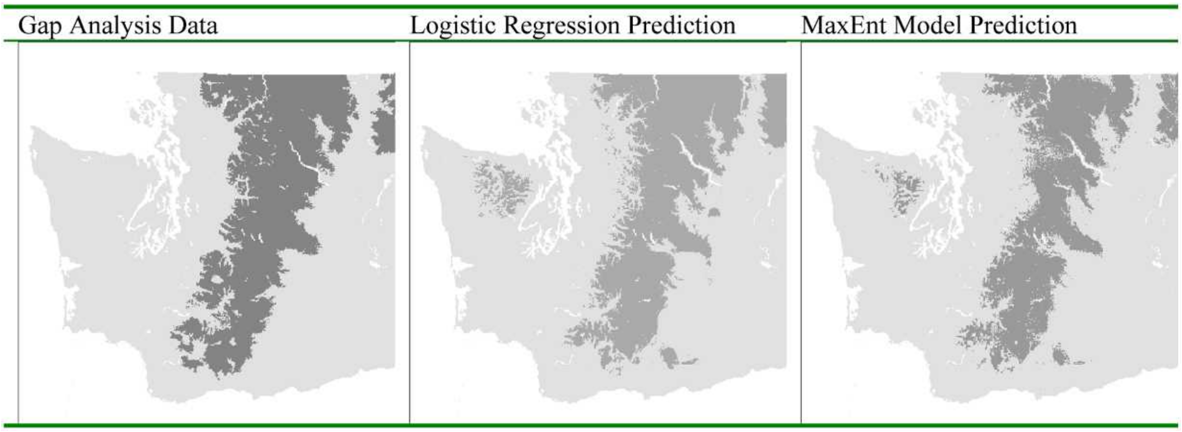


Fig. 2. Original (current) distribution of the wolverine matches predicted current distributions from the logistic regression and MaxEnt model well, using a 0.5 (50%) probability threshold.

bility threshold of 0.5. Higher specificity for the MaxEnt model suggests that this model is conservative by not over-predicting species presence, but in contrast may be under-predicting presence.

Future projections—range size

For illustration, the projected future range for the wolverine under one warming scenario is shown in Fig. 3 (see Appendix C for maps of all projections for all species). Projected trends (Fig. 4) indicate that climate change may result in significant loss in geographic range size of higher elevation species, and this trends holds across all models and scenarios (Table 3). Both models projected that the high and mid elevation species (American pika, hoary marmot and mountain goat and wolverine) would experience the greatest range losses with up to 80% range loss by the end of the century for these species (Fig. 4), while the lynx is projected to virtually disappear from the focal

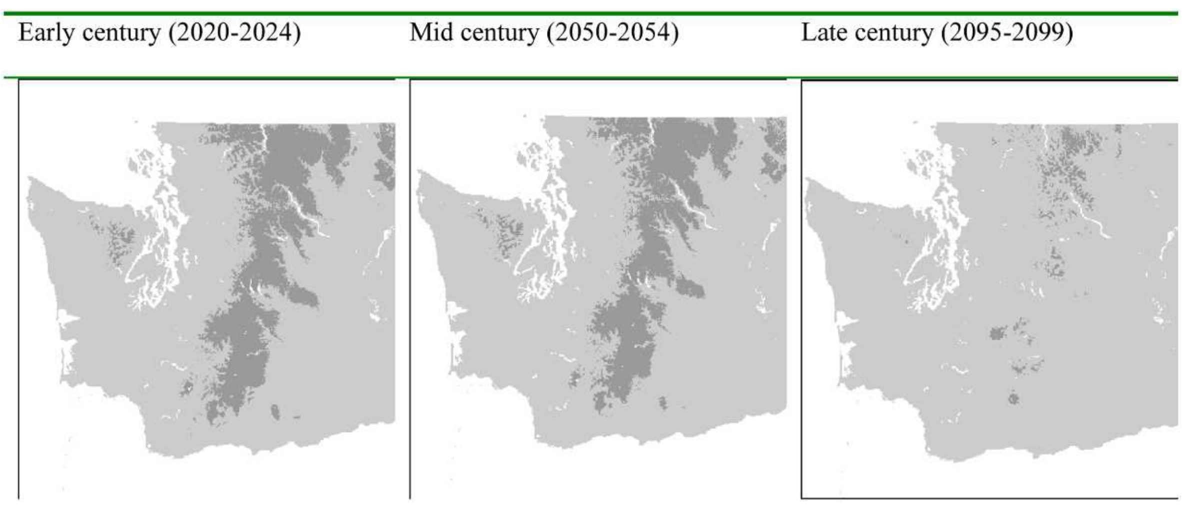


Fig. 3. Example of a projected range distribution of the wolverine for the early, mid, and late century, all under the MaxEnt model based on the Hadley data and the "high" (A2) carbon emission scenario. See Appendix C for projections for all species under all emissions scenarios and species distribution models.

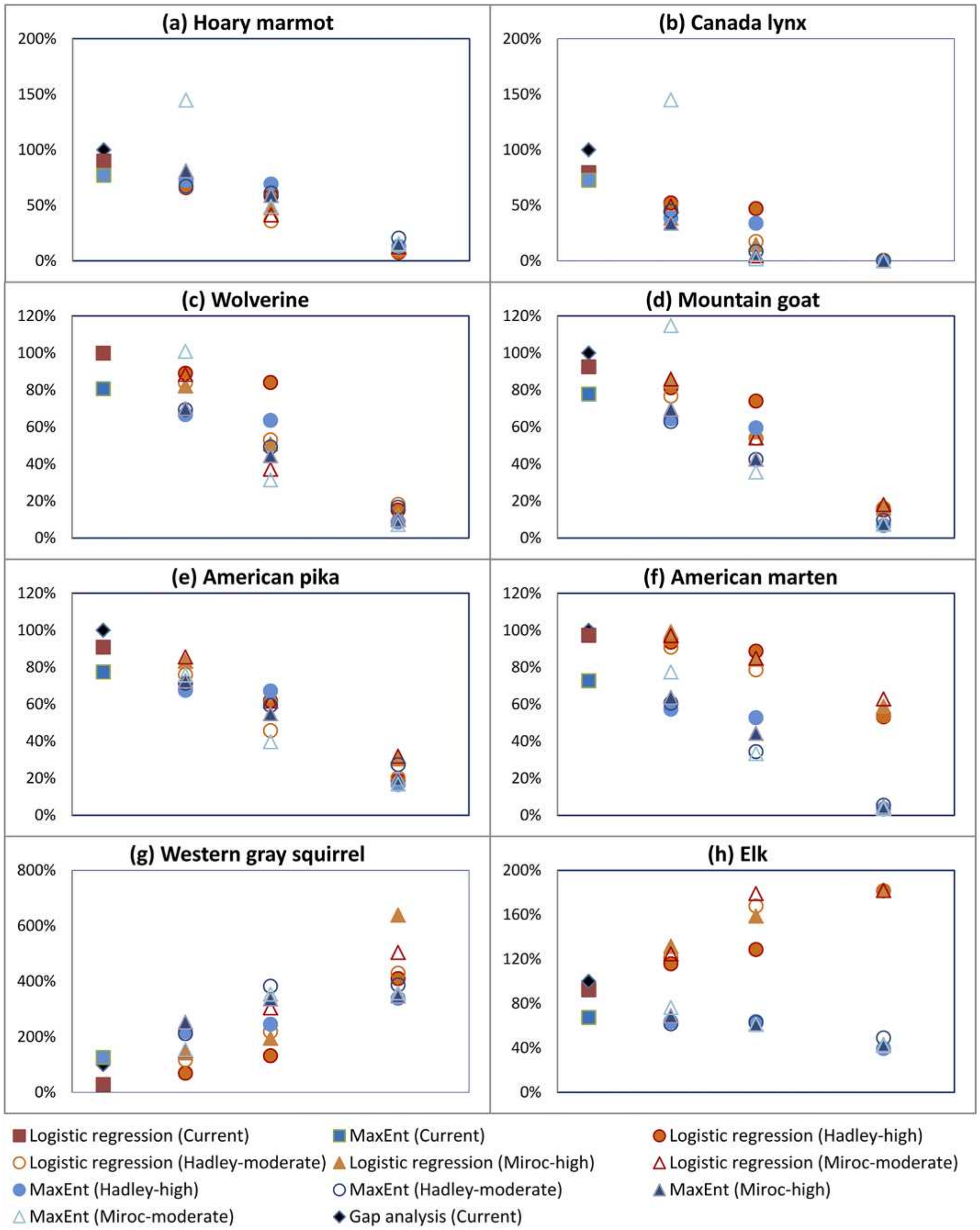


Fig. 4. For each modeled climate change scenario, the predicted range size expressed as a percentage of the original Gap Analysis range is shown.

Table 3. Tests for significant trends in range size loss or gain for each species, under the MaxEnt and logistic regression distribution models and both models combined. The t-test compares regression model slopes to determine consistency of the different models to project trends. No significant difference means the models give congruent insights.

Species	Both models R^2	Both models P	MaxEnt R^2	MaxEnt P	Logistic regression R^2	Logistic regression P	*t*-test model difference P
Hoary marmot	0.773	<0.001	0.660	0.001	0.953	<0.001	No, >0.05
Canada lynx	0.612	<0.001	0.470	0.01	0.827	<0.001	No, >0.05
Wolverine	0.901	<0.001	0.852	<0.001	0.871	<0.001	No, >0.05
Mountain goat	0.857	<0.001	0.797	<0.001	0.947	<0.001	No, >0.05
American pika	0.906	<0.001	0.892	<0.001	0.927	<0.001	No, >0.05
American marten	0.502	<0.001	0.928	<0.001	0.902	<0.001	Yes, <0.005
Western gray squirrel	0.713	<0.001	0.697	<0.001	0.844	<0.001	Yes, <0.005
Elk	0.029	>0.1	0.792	<0.001	0.830	<0.001	Yes, <0.001

area by 2100. There were no significant differences between range loss projections from the MaxEnt and logistic regression models for these species, and trends were consistent across global climate models (Hadley vs. Miroc) and emission scenarios (A2 vs. A1B) as well (Table 3).

For lower elevation species including the American marten, western gray squirrel, and the elk, the picture is more complicated. While trends were consistent between global climate models and emission scenarios, there were significant differences between projections generated by the MaxEnt and logistic regression models for these species (Table 3). For the American marten, both models predict significant range loss, but MaxEnt predicts a rapid reduction to more than 90% loss by the end of the century. In contrast, the logistic regression projects a more gradual decline to approximately 40% loss by 2100. For the western gray squirrel, both models project large range expansion over the next century (Table 3). However, MaxEnt projected a more gradual increase in range size than the logistic regression model. For the elk, the models disagree as to whether the range is likely to expand or contract over time. MaxEnt projects significant declines in range size (Table 3), while the logistic regression model projects a significant increase in range size. This translates to a near doubling of the range across all warming scenarios and an expansion across virtually the entire focal area. Due to these opposite trend projections, model disagreement is highest for this species.

Future projections—elevation shifts

Both the logistic regression and MaxEnt models predict that the average elevation of most species' ranges will significantly increase over the coming century (Fig. 5). This trend was consistent across both the Hadley and Miroc global climate model data, using the A2 or "high emission" scenario. The species projected to increase most significantly in average elevation is the Canada lynx (Fig. 5). For all other species where ranges are projected to significantly contract (hoary marmot, wolverine, mountain goat, American pika, and American marten), their elevation is also projected to rise significantly ($P < 0.001$) over the next century (Fig. 5).

In contrast, there are no significant trends for the lower elevation species: the average elevation of the western gray squirrel is not expected to change, while models once again disagree with regards to projections for the elk. While the MaxEnt model predicts significant elevation gain similar to patterns seen for the higher elevation species, the logistic regression model predicts no rise in average elevation, and even a potential decline.

Discussion

This study examines the potential fate of mammal species in Cascadia's parks under projected climate warming over the next century. The clearest emerging trend is that range losses are projected for the higher elevation mammal species considered here, including the hoary marmot, Canada lynx,

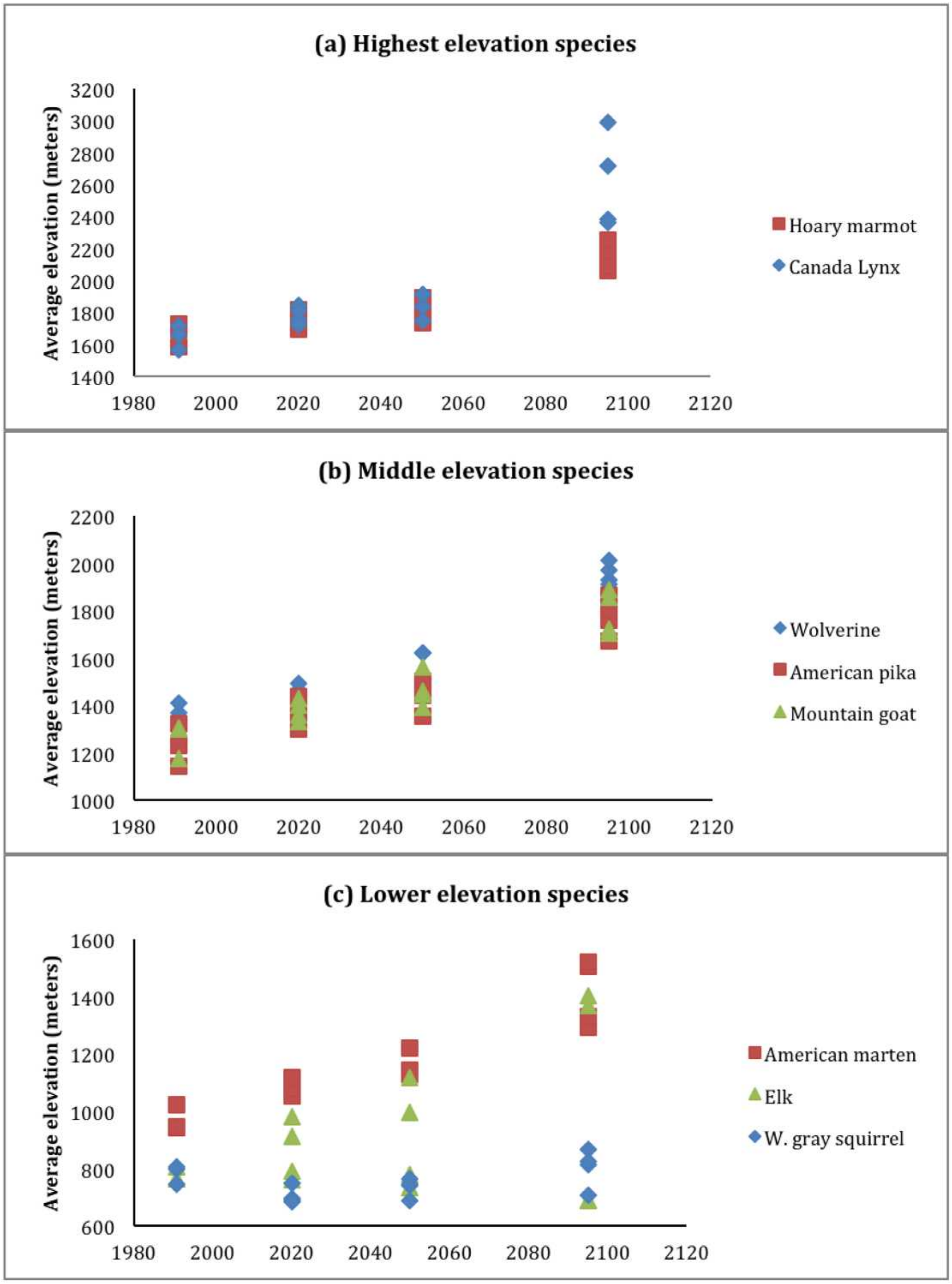


Fig. 5. Predicted elevation of the range of the (a) highest elevation, (b) middle elevation, and (c) lower elevation species over time, from logistic regression and MaxEnt species distribution models, run using both the Hadley and Miroc global climate models under the A2 carbon emission scenario. Values are species averages calculated from outputs of logistic regression and MaxEnt approaches for different GCM scenarios.

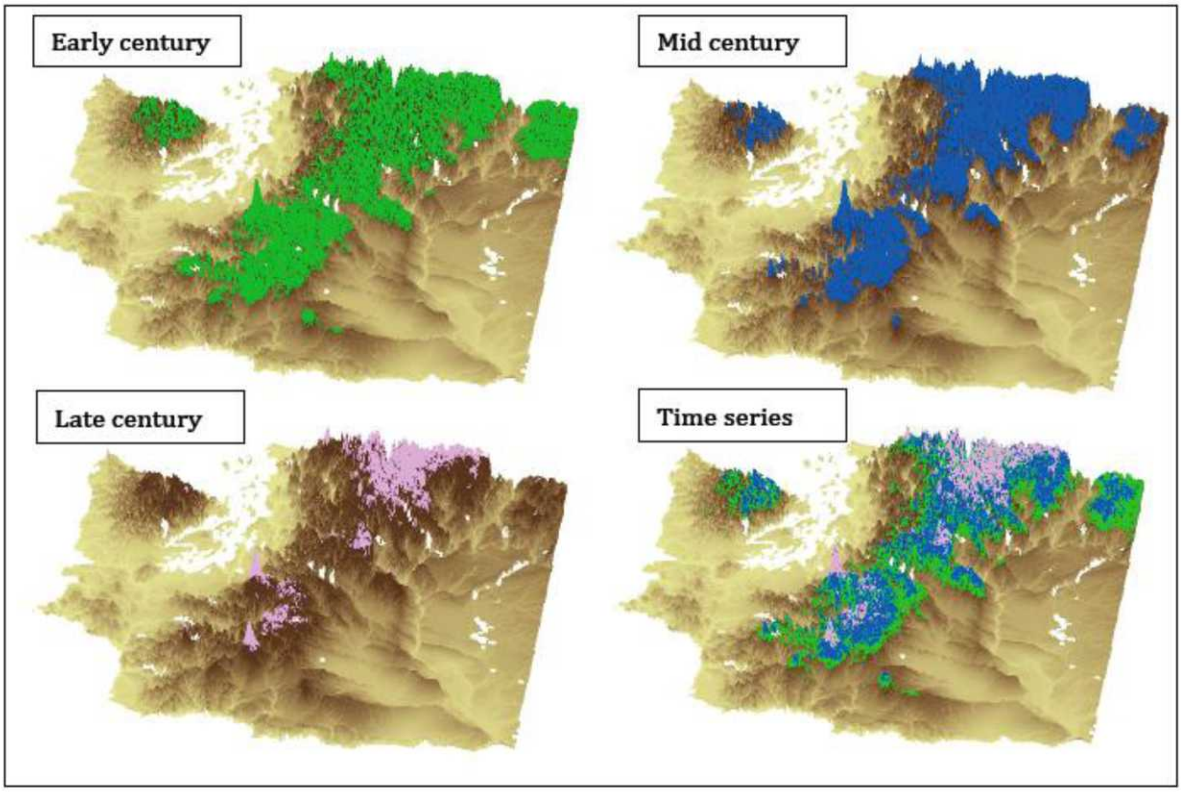


Fig. 6. Three-dimensional illustration of predicted range shifts of the wolverine over time, with a composite illustration at lower right. Elevations are exaggerated for ease of viewing. From the logistic regression model under the Miroc global climate model using the high/A2 emission scenario.

wolverine, American pika, and mountain goat. Both species distribution models agree that the future ranges of these mammals in our focal area are likely to be smaller by the end of the century than they are today, across all warming scenarios. Trends are quite consistent between species: ranges are projected to shrink by as much as 80% or more by 2100, and are projected to become more fragmented and isolated as well. However, there is little evidence of range shifting into new, previously unoccupied areas for these species within the focal cascades region (Appendix C). Instead, projected ranges appear to shrink inward toward the core areas over time. In addition, one species (the Canada lynx) was projected to be virtually absent from this area by 2100. Whether or not species are able to move beyond this region into Canada remains uncertain and requires further analyses that are beyond the goals of the current assessment.

The picture for the lower elevation species we analyzed, including the American marten, western gray squirrel, and the elk is somewhat more complicated. Projections differ somewhat between the logistic regression model and the MaxEnt model. Generally, both models project little range loss for these more widespread and generalist species, and that some species may expand their ranges over the next century, especially in the eastern portion of our focal area.

For most species we examined, including the five higher elevation species as well as the American marten, the second clear trend is that as ranges shrink over time, species are projected to retreat further upwards into even higher elevation areas. Rates of increase are relatively consistent across models at approximately 50 (40–60) meters of elevation gain per decade over the next century, with only the Canada lynx projected to increase in elevation more rapidly as its range virtually disappears. For these species, we should expect range loss to occur primarily in the lower elevation portions of each species' range, while the highest alpine areas are more likely to serve as refuges that will continue to support species over time (e.g., see Fig. 6). In contrast, significant elevation shifts are not projected for the lower elevation species (elk and western gray squirrel), as they are projected to expand their range into other low elevation areas.

Future projections of climate change carry high degrees of uncertainty because disparate data sources that are used in the projections vary in their degree of uncertainty (e.g., modeled climate data are less certain that empirically measured or expert opinion-based geographic range data). Moreover, the projections are difficult to validate because effects of climate change over then next century is an ongoing experiment. We have, however, taken several measures to constrain the "unreliability" of our projections. First, we used only those environmental variables that are deemed by the Washington State GAP program to be biologically important and meaningful for the focal species. We used two modeling approaches that have different assumptions about species detectability (presence/absence vs. presence only), and differ in the algorithms used to project future geographic range distributions. We ensured model validity by making sure that the projections for species' current geographic ranges aligned with actual current geographic ranges; and we did this for both modeling approaches (Appendix B). We then used the same coefficients to project future species distributions using biophysical landscape data from the climate change models. Because insights from these approaches were generally congruent, we can place some faith in the reliability of the projections. Of course, any modeling such as this ultimately only provides heuristic value through presentation of plausible scenarios, and so management aimed at land-use planning for climate adaptation should use such assessments with complementary insight from other studies that have measured climate effects over recent history within the study region (e.g., Moritz et al. 2008, Barnosky 2009). Using information from multiple modeling approaches and empirical data allows one to assign higher levels of confidence where the insights are congruent and explore further with additional analysis and data where they disagree (Lawler et al. 2010). A potentially confounding factor, that remains highly uncertain, is how the changing human built environment in consequence to the need to adapt to climate change will alter the geographic distribution of species within the Cascadia landscape. Developing such insights would enable updating projections by changing the value of the variables distance to roads and cities.

National Parks as high elevation refuges

Based on the projected future range distributions from both models and across all warming scenarios, we found that in general the primary national parks in our focal area—Olympic, Mount Rainier and North Cascades—are likely to remain important refuges for these high elevation mammal species throughout the next century, even as ranges could dramatically decline in size. The fact that these parks are located in some of the highest elevation regions of the focal area may assist in their ability to support and maintain these high elevation species over time, though complete losses of certain species from these refuges are still projected. We should note that we looked only at whether models projected species presence in a particular park by the end of the century based on geographic distribution only. However, no analyses on the amount of contiguous range or habitat or other environmental variables necessary to support viable populations within those geographic ranges were performed. Such analyses might include more focused analyses on how snowfall levels and seasonal, rather than annual, temperatures (Wang et al. 2002, White et al. 2011). In addition, we do not account for the geographic distribution of prey species of the predators examine here. While this kind of analysis has been called for (Schmitz et al. 2003), the spatial modeling tools and data resolution needed to evaluate such interactions to understand species viability do not yet exist for this region.

Our models project that Mount Rainier National Park, with the highest average elevation of approximately 1580 meters, is likely to continue to support the high elevation species considered here (hoary marmot, wolverine, mountain goat, American pika, and American marten) throughout this century, even as their ranges shrink elsewhere. Mount Rainier could even serve as one of the last refuges in the state for the Canada lynx, which is projected to almost completely disappear from the rest of the focal area by the end of the century. This park is also projected to support an increasing amount of elk range as it expands over time.

Similarly, North Cascades National Park, with an average elevation of approximately 1460 meters, is also projected to continue to support all high elevation species considered here, with the exception of the lynx. It is also likely to include a greater amount of elk range over time. While the initial Western gray squirrel range was only marginally included in the park, models project future expansion eastward away from the park boundaries.

Finally, the Olympic National Park, with a somewhat lower average elevation of approximately 950 meters, may be more likely to lose certain high elevation species as their ranges contract upwards. While the park is projected to continue to contain the range of the mountain goat, American pika, and American marten, models project only very scattered remnant portions (if any) of hoary marmot and wolverine range, and a likely loss of lynx range by the end of the century. Again, Olympic National Park is projected to support elk throughout the next century.

Implications

Our analysis provides a range of possible future scenarios for how high and mid-elevation mammal species may react to climate change over the coming century, and are intended to assist in planning for the future management of these species of conservation concern. The maps provided in Appendices B and C illustrate these possible scenarios, but the consistent trends are likely to be more informative for managers than individual projections. While only eight species were analyzed, our results suggest that trends for even unrelated high elevation mammals seem to be largely consistent between species. Our results confirm speculation (Barnosky 2009) and previous analyses (Burns et al. 2003) that montane national parks and protected areas will require special attention under climate change. To this end, managers may want to prioritize conservation activities in high elevation areas that are likely to serve as future refuges for these species, over lower elevation areas that may become less suitable over time (Baron et al. 2009). Finally, it may make sense to prioritize efforts either toward species such as the Canada lynx, hoary marmot, or American pika which are projected to lose significant range area over lower elevation species such as the elk or western gray squirrel, which may be less likely to lose significant range area under climate change.

Acknowledgments

Funding support was provided by the North Cascades National Park Service Complex, the Doris Duke Foundation, and Yale University. We than Mark Janikas for help with integrating GIS and the R environment and data analysis. Sincere thanks to Brendan Rogers, Ray Drapek, and Ron Neilson from Oregon State University for generously sharing modeled vegetation and climate data, and to Walter Jetz, Dana Tomlin and anonymous reviewers for providing comments and advice. We also thank Regina Rochefort from the North Cascades National Park for her research support, time, and encouragement. The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the U.S. Fish and Wildlife Service.

Literature Cited

Araújo, M. B., M. Cabezza, W. Thuiller, L. Hannah, and P. H. Williams. 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. Global Change Biology 10:1618–1626.

Bachelet, D., R. P. Neilson, J. M. Lenihan, and R. J. Drapek. 2001. Climate change effects on vegetation distribution and carbon budget in the United States. Ecosystems 4:164–185.

Barnosky, A. D. 2009. Heatstroke: nature in an age of global warming. Island Press, Washington, D.C., USA.

Baron, J. S., L. Gunderson, C. D. Allen, E. Fleishman, D. McKenzie, L. A. Myerson, J. Oropeza, and N. Stephenson. 2009. Options for national parks and reserves for adapting to climate change. Environmental Management 44:1033–1042.

Burns, C. E., K. M. Johnston, and O. J. Schmitz. 2003. Global climate change and mammalian species diversity in US national parks. Proceedings of the National Academy of Sciences USA 100:11474–11477.

Elith, J., C. H. Graham, R. P. Anderson, M. Dudik, S. Ferrier, A. Guisan, R. J. Hijmans, et al. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29:129–51.

Elsner, M. M. 2009. Washington State Climate Change Impacts Assessment: HB 1303 Key Findings presented at the Washington Climate Change Impacts Assessment Conference, February 12, Washington State Convention Center, Seattle, Washington, USA.

ESRI [Environmental Systems Research Institute]. 2009. ArcGIS 9.3.1. Environmental Systems Research Institute, Redlands, California, USA.

Fielding, A. H. and J. F. Bell. 1997. A review of methods for the assessment of prediction error in conservation presence/absence models. Environmental Conservation 24:38–49.

Guisan, A. and W. Thuiller. 2005. Predicting species distribution: offering more than simple habitat models. Ecology Letters 8:993–1009.

Guisan, A. and N. E. Zimmerman. 2000. Predictive habitat distribution models in ecology. Ecological Modelling 135:147–186.

Hannah, L., G. Midgley, S. Andelman, M. Araujo, G. Hughes, E. Martinez-Meyer, R. Pearson, and P. Williams. 2007. Protected area needs in a changing climate. Frontiers in Ecology and the Environment 5:131–138.

Hasumi, H., and S. Emori. 2004. K-1 Coupled GCM (MIROC) description. K-1 Model Developers Technical Report 1. Center for Climate System Research, University of Tokyo, Tokyo, Japan.

IPCC [Intergovernmental Panel on Climate Change]. 2000. Special report on emissions scenarios, Working Group III. Cambridge University Press, Cambridge, UK.

Johns, T. C., J. M. Gregory, W. J. Ingram, C. E. Johnson, A. Jones, J. A. Lowe, J. F. B. Mitchell, et al. 2003. Anthropogenic climate change for 1860 to 2100 simulated with the HadCM3 model under updated emissions scenarios. Climate Dynamics 20:583–612.

Johnson, R. E., and K. M. Cassidy. 1997. Terrestrial mammals of Washington State: Location data and predicted distributions. Volume 3. *In* K. M. Cassidy, C. E. Grue, M. R. Smith, and K. M. Dvornich, editors. Washington State Gap Analysis: Final Report. Washington Cooperative Fish and Wildlife Research Unit, University of Washington, Seattle, Washington, USA.

Johnston, K. M. and O. J. Schmitz. 1997. Influence of climate change on the distribution of selected wildlife species within the continental USA. Global Change Biology 3:531–544.

LaSorte, F. A. and W. Jetz. 2010. Projected range contractions of montane biodiversity under global warming. Proceedings of the Royal Society of London B 277:3401–3410.

Lawler, J. J., T. H. Tear, C. Pyke, M. R. Shaw, P. Gonzalez, P. Kareiva, L. Hansen, L. Hannah, K. Klausmeyer, A. Aldous, C. Bienz, and S. Pearsall. 2010. Resource management in a changing and uncertain climate. Frontiers in Ecology and the Environment 8:35–43.

Lovejoy, T. E. and L. Hannah. 2006. Climate change and biodiversity. Yale University Press, New Haven, Connecticut, USA.

Malcolm, J. R., C. R. Liu, R. P. Neilson, L. Hansen, and L. Hannah. 2006. Global warming and extinctions of endemic species from biodiversity hotspots. Conservation Biology 20:538–48.

Moritz, C., J. L. Patton, C. J. Conroy, J. L. Parra, G. C. White, and S. R. Beissinger. 2008. Impact of a century of climate change on small-mammal communities in Yosemite National Park, USA. Science 322:261–264.

NPSpecies. 2009. The National Park Service Biodiversity Database. https://science1.nature.nps.gov/npspecies/web/main/start

Parmesan, C. 2006. Ecological and evolutionary responses to recent climate change. Annual Review of Ecology, Evolution and Systematics 37:637–669.

Pearce, J. and S. Ferrier. 2000. Evaluating the predictive performance of habitat models developed using logistic regression. Ecological Modelling 133:225–245.

Peters, R. and J. Darling. 1985. The greenhouse effect and nature reserves. BioScience 35:707–716.

Rogers, B. M. 2009. Potential impacts of climate change on vegetation distributions, carbon stocks, and fire regimes in the U.S. Pacific Northwest. Thesis. Oregon State University, Corvallis, Oregon, USA.

Rogers, B. M., R. P. Neilson, R. Drapek, J. M. Lenihan, J. R. Wells, D. Bachelet, and B. E. Law. 2011. Impacts of climate change on fire regimes and carbon stocks of the U.S. Pacific Northwest. Journal of Geophysical Research 116:G03037.

Schmitz, O. J. E. Post, C. E. Burns, and K. M. Johnston. 2003. Ecosystem responses to global climate change: moving beyond color-mapping. BioScience 53:1199–1205.

Theurillat, J. P. and A. Guisan. 2001. Potential impact of climate change on vegetation in the European Alps: A review. Climatic Change 50:77–109.

USGS National Map Seamless Server. 2009. 1-Arc Second National Elevation Dataset, USGS Earth Resources Observation & Science (EROS) Center. http://seamless.usgs.gov/

Walther, G.-R. 2010. Community and ecosystem responses to recent climate change. Philosophical Transactions of the Royal Society B 356:2019–2024.

Wang, G., N. Thompson Hobbs, F. J. Singer, D. S. Ojima, and B. C. Lubow. 2002. Impacts of climate changes on elk population dynamics in Rocky Mountain National Park, Colorado, U.S.A. Climatic Change 54:205–223.

WSDOT. 2010. Washington Department of Transportation GeoData Distribution Catalog. GIS/Cartography Section, Washington State Department of Transportation, Olympia, Washington, USA. http://www.wsdot.wa.gov/mapsdata/geodatacatalog/default.htm#main

WDFW. 2008. Priority habitat and species list. Washington Department of Fish and Wildlife, Olympia, Washington, USA.

White, K. S., G. W. Pendleton, D. Crowley, H. J. Griese, K. J. Hundertmark, T. McDonough, L. Nichols, M. Robus, C. A. Smith, and J. W. Schoen. 2011. Mountain goat survival in coastal Alaska: Effects of age, sex, and climate. Journal of Wildlife Management 75:1731–1744.

Supplemental Material

Appendix A

Table A1. Regression coefficients for the 15 environmental variables used in logistic regression models to predict eight montane mammal species range distributions.

Variable	Coefficient	SE	Significance probability
American marten			
Intercept	0.485097	0.716093	0.498139
tmp1991	−0.417109	0.048341	0.000000
ppt1991	0.010308	0.000544	0.000000
veg8_10	0.239035	0.495726	0.629670
veg7_10	0.662336	0.488013	0.174715
veg6_10	−2.786528	0.512850	0.000000
veg2_10	−6.531055	0.612250	0.000000
veg17_10	−0.743395	0.523548	0.155632
veg16_10	−3.189199	0.621198	0.000000
veg12_10	−0.191953	0.552853	0.728438
veg10_10	7.902377	105.414358	0.940243
slope	0.032844	0.002796	0.000000
elevation	0.000051	0.000216	0.813365
aspect	−0.000023	0.000286	0.937105
disthigh	0.000002	0.000005	0.595026
distcity	0.000039	0.000003	0.000000
American pika			
Intercept	1.117310	0.765029	0.144158
tmp1991	−0.480580	0.047673	0.000000
ppt1991	0.002653	0.000472	0.000000
veg8_10	−0.284804	0.579299	0.622978
veg7_10	1.122645	0.575708	0.051173
veg6_10	−0.618755	0.596094	0.299263
veg2_10	−3.802801	0.648612	0.000000
veg17_10	−1.085374	0.618826	0.079444
veg16_10	−4.355516	0.913900	0.000002
veg12_10	−1.125377	0.651992	0.084337
veg10_10	10.932915	200.589043	0.956534
slope	0.018221	0.002701	0.000000
elevation	0.001217	0.000214	0.000000
aspect	0.000112	0.000296	0.704660
disthigh	−0.000027	0.000005	0.000000
distcity	0.000014	0.000003	0.000000
Canada lynx			
Intercept	6.568681	0.995249	0.000000
tmp1991	−1.154056	0.085560	0.000000
ppt1991	−0.023077	0.001559	0.000000
veg8_10	0.516895	0.354187	0.144460
veg7_10	−2.484888	0.510547	0.000001

Table A1. Continued.

Variable	Coefficient	SE	Significance probability
veg6_10	0.002095	0.405013	0.995872
veg2_10	−1.093918	0.535604	0.041112
veg17_10	−0.651225	0.544192	0.231430
veg16_10	−1.265681	0.619958	0.041195
veg12_10	−1.893900	93.852530	0.983900
veg10_10	0.056149	0.005028	0.000000
slope	−0.002244	0.000401	0.000000
elevation	−0.000575	0.000560	0.303858
aspect	0.000032	0.000007	0.000001
disthigh	0.000042	0.000005	0.000000
distcity	6.568681	0.995249	0.000000
Elk			
Intercept	−14.205008	0.770438	0.000000
tmp1991	0.853241	0.053620	0.000000
ppt1991	0.036901	0.001087	0.000000
veg8_10	1.015124	0.449070	0.023790
veg7_10	0.127290	0.437860	0.771274
veg6_10	−2.623861	0.475970	0.000000
veg2_10	−6.473873	0.662417	0.000000
veg17_10	2.960567	0.463926	0.000000
veg16_10	0.550910	0.447559	0.218352
veg12_10	0.539418	0.509085	0.289334
veg10_10	1.818501	60.704361	0.976102
slope	0.016606	0.003111	0.000000
elevation	0.004707	0.000269	0.000000
aspect	−0.000649	0.000278	0.019441
disthigh	0.000008	0.000005	0.097126
distcity	0.000025	0.000003	0.000000
Gray squirrel			
Intercept	−8.227370	0.938328	0.000000
tmp1991	0.574669	0.075230	0.000000
ppt1991	−0.027103	0.002156	0.000000
veg8_10	1.372453	0.295805	0.000003
veg7_10	0.527046	0.345235	0.126853
veg6_10	−0.093754	0.511439	0.854551
veg2_10	−3.488608	6.744762	0.604994
veg17_10	2.001335	0.306631	0.000000
veg16_10	−1.816991	0.313380	0.000000
veg12_10	−1.510794	78.152858	0.984577
veg10_10	0.024453	0.004490	0.000000
slope	0.002273	0.000371	0.000000
elevation	−0.000463	0.000446	0.298453
aspect	−0.000002	0.000007	0.733603
disthigh	0.000021	0.000005	0.000050
distcity	−8.227370	0.938328	0.000000
Hoary marmot			
Intercept	−3.862441	0.797812	0.000001
tmp1991	−0.631301	0.066122	0.000000
ppt1991	0.003594	0.000611	0.000000
veg8_10	2.235676	0.306777	0.000000
veg7_10	2.806007	0.314874	0.000000
veg6_10	2.587150	0.286182	0.000000
veg2_10	1.753453	0.701775	0.012469
veg17_10	13.051071	34.836342	0.707929
veg16_10	0.017655	0.003774	0.000003
veg12_10	0.001349	0.000317	0.000021
veg10_10	−0.000265	0.000452	0.557421
slope	0.000001	0.000006	0.811576
elevation	0.000030	0.000004	0.000000
aspect	−3.862441	0.797812	0.000001
disthigh	−0.631301	0.066122	0.000000
distcity	0.003594	0.000611	0.000000
Mountain goat			
Intercept	3.666304	0.808878	0.000006
tmp1991	−0.771135	0.053473	0.000000
ppt1991	0.010422	0.000565	0.000000
veg8_10	−0.204171	0.584760	0.726974
veg7_10	−0.267074	0.579144	0.644689

Table A1. Continued.

Variable	Coefficient	SE	Significance probability
veg6_10	−0.010150	0.612262	0.986773
veg2_10	−4.151078	0.663605	0.000000
veg17_10	−0.564655	0.627358	0.368093
veg16_10	−3.059676	0.822157	0.000198
veg12_10	−0.636302	0.666287	0.339580
veg10_10	9.464514	218.078353	0.965383
slope	0.050502	0.002975	0.000000
elevation	−0.000754	0.000234	0.001269
aspect	−0.000103	0.000326	0.753056
disthigh	−0.000038	0.000005	0.000000
distcity	0.000021	0.000002	0.000000
Wolverine			
Intercept	9.595857	1.030067	0.000000
tmp1991	−1.282120	0.067181	0.000000
ppt1991	−0.003687	0.000620	0.000000
veg8_10	0.426121	0.760436	0.575231
veg7_10	−0.560821	0.758949	0.459941
veg6_10	−2.077028	0.783944	0.008062
veg2_10	−2.941375	1.291093	0.022714
veg17_10	−0.496024	0.778692	0.524127
veg16_10	−1.740473	0.788057	0.027205
veg12_10	0.557113	0.793265	0.482490
veg10_10	−7.103907	70.353999	0.919571
slope	0.016223	0.003485	0.000003
elevation	−0.000674	0.000294	0.021970
aspect	−0.000555	0.000394	0.158467
disthigh	−0.000062	0.000006	0.000000
distcity	0.000049	0.000004	0.000000

Notes: Abbreviations are: Tmp1991 = mean annual 1991 temperature; ppt1991 = mean annual 1991 precipitation; vegetation type: 2 = tundra; 6 = subalpine forest; 7 = maritime evergreen needleleaf forest; 8 = temperate evergreen needleleaf forest; 10 = temperate cool mixed forest; 12 = temperate evergreen needleleaf woodland; 16 = temperate shrubland; 17 = temperate grassland; disthigh = distance to highway; distcity = distance to city.

APPENDIX B

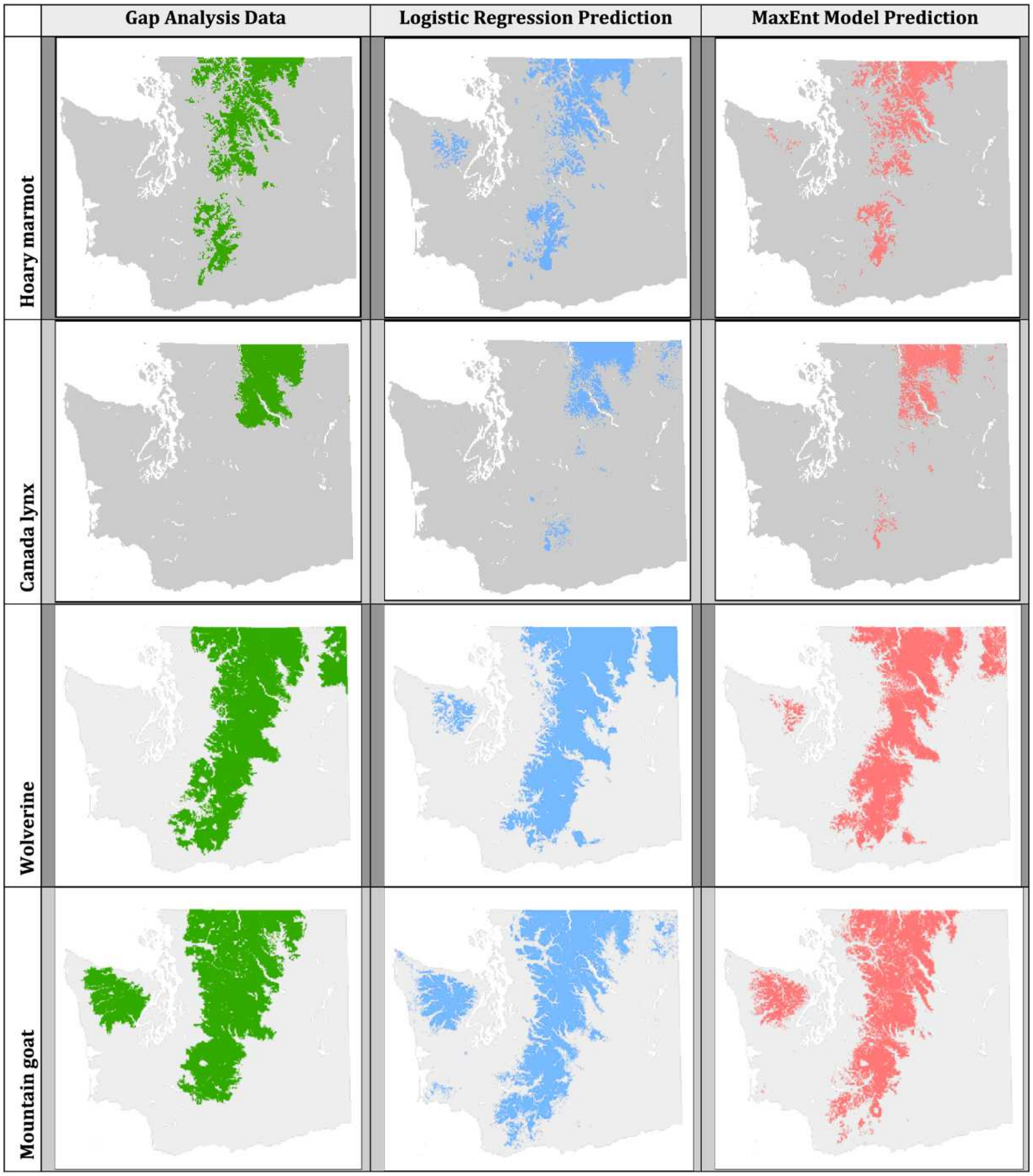


Fig. B1. Comparison of original mammal species range distribution data (Washington State Gap Analysis Project) and predicted distributions for present day (1991) under two species distribution models. The data validate the reliability of the distribution modeling approaches to explain current distributions. There are three images for each species (current observed distributions and current predicted using logistic regression and maximum entropy[MaxEnt]).

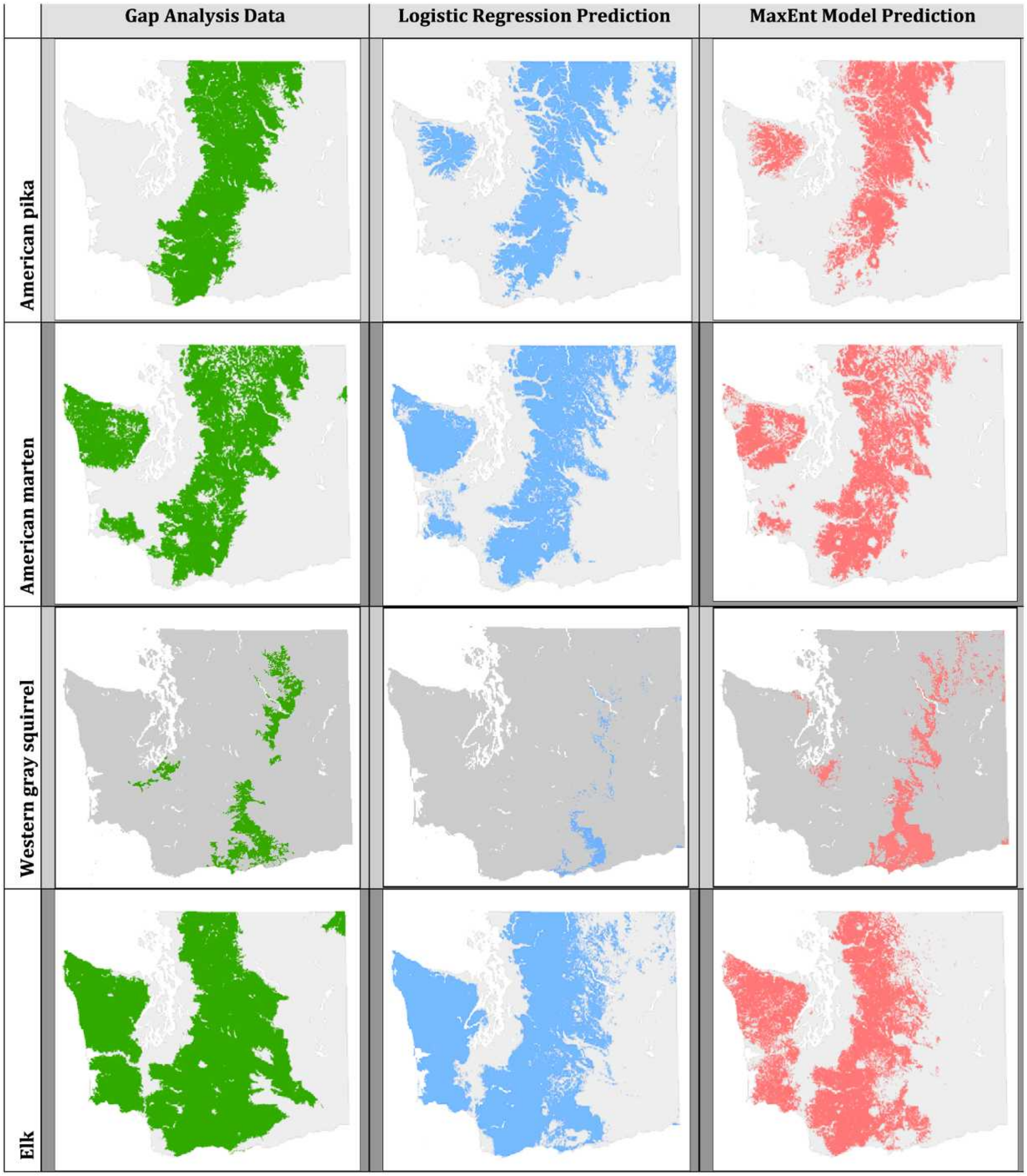
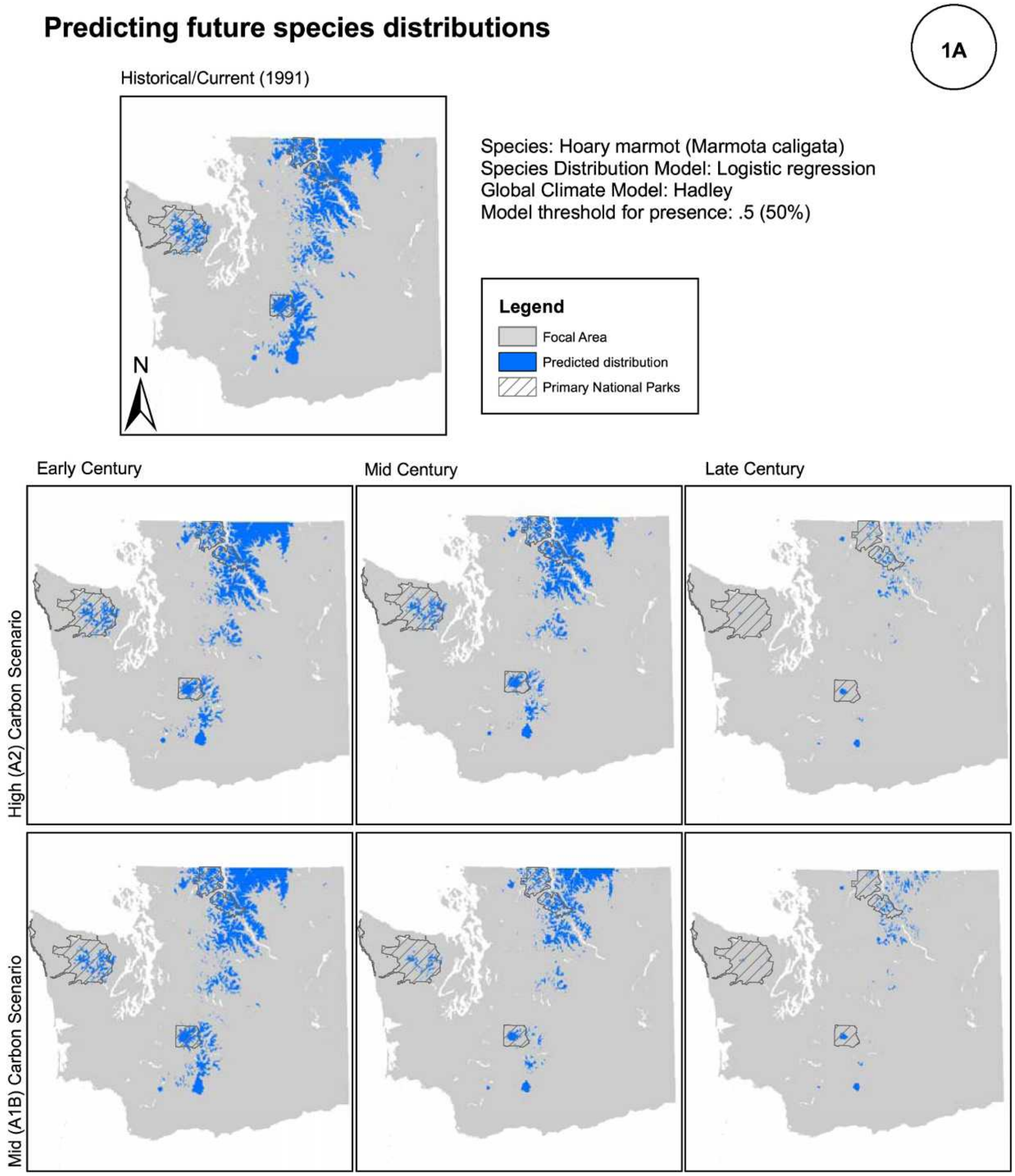


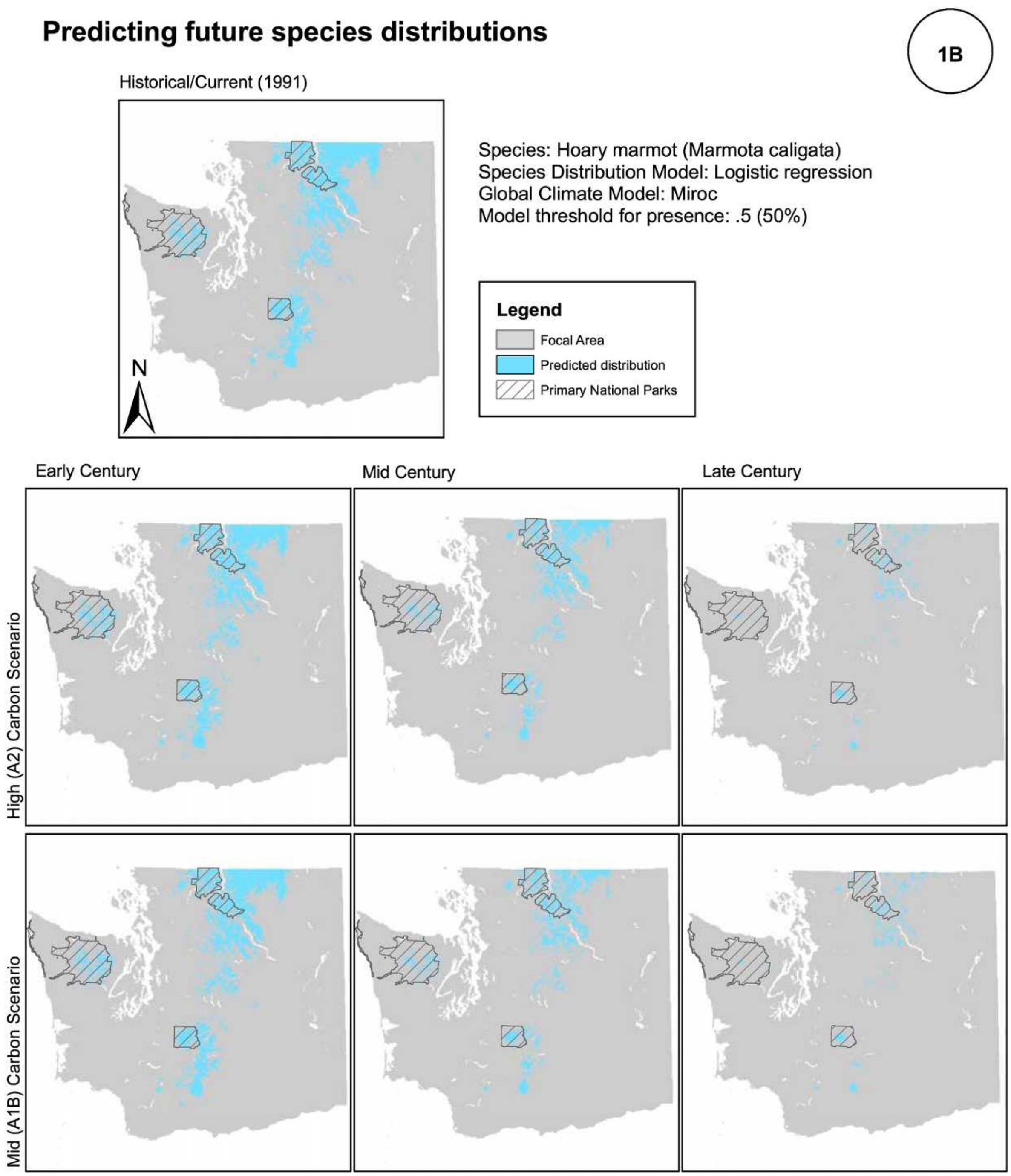
Fig. B1 (continued).

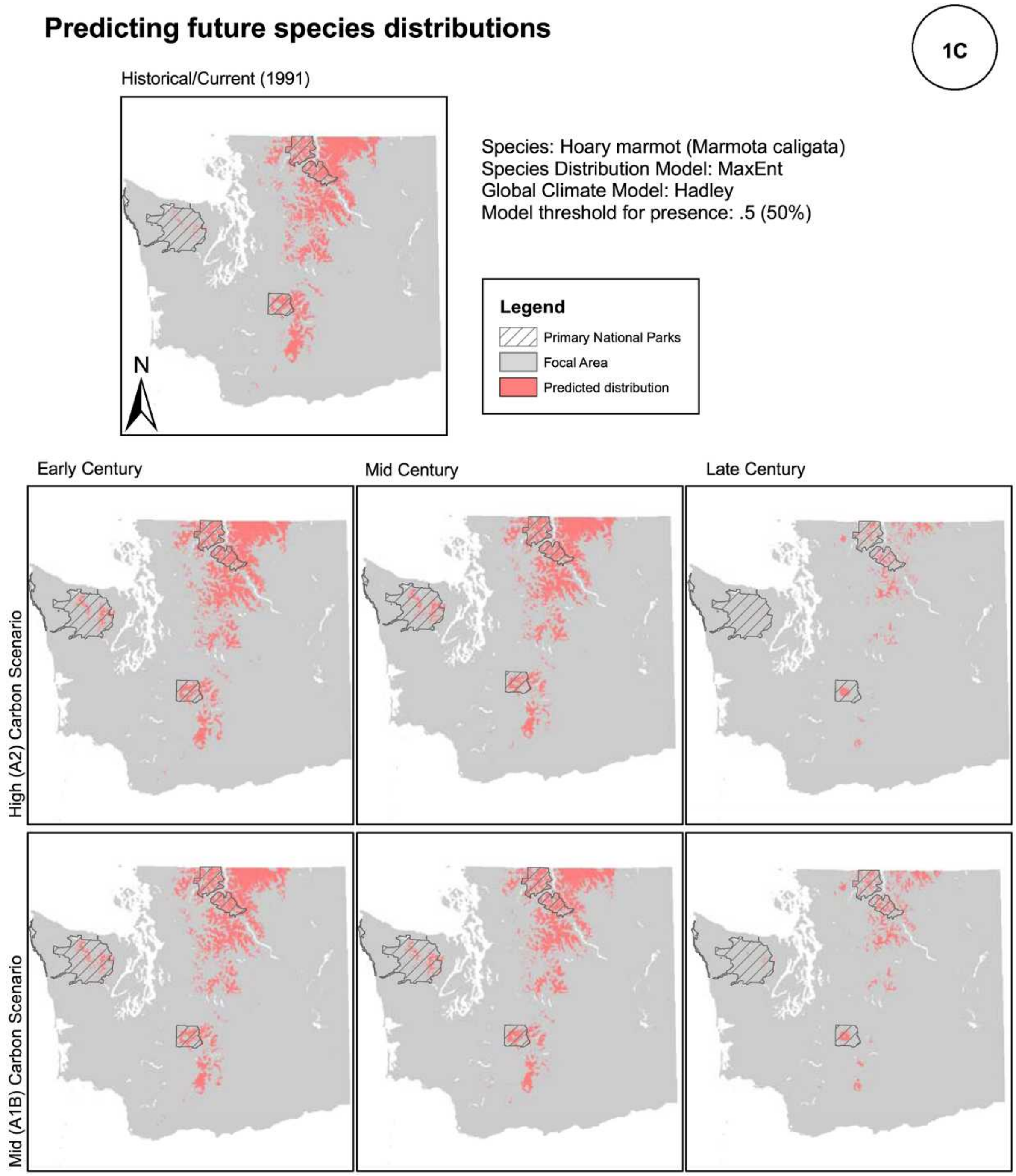
APPENDIX C

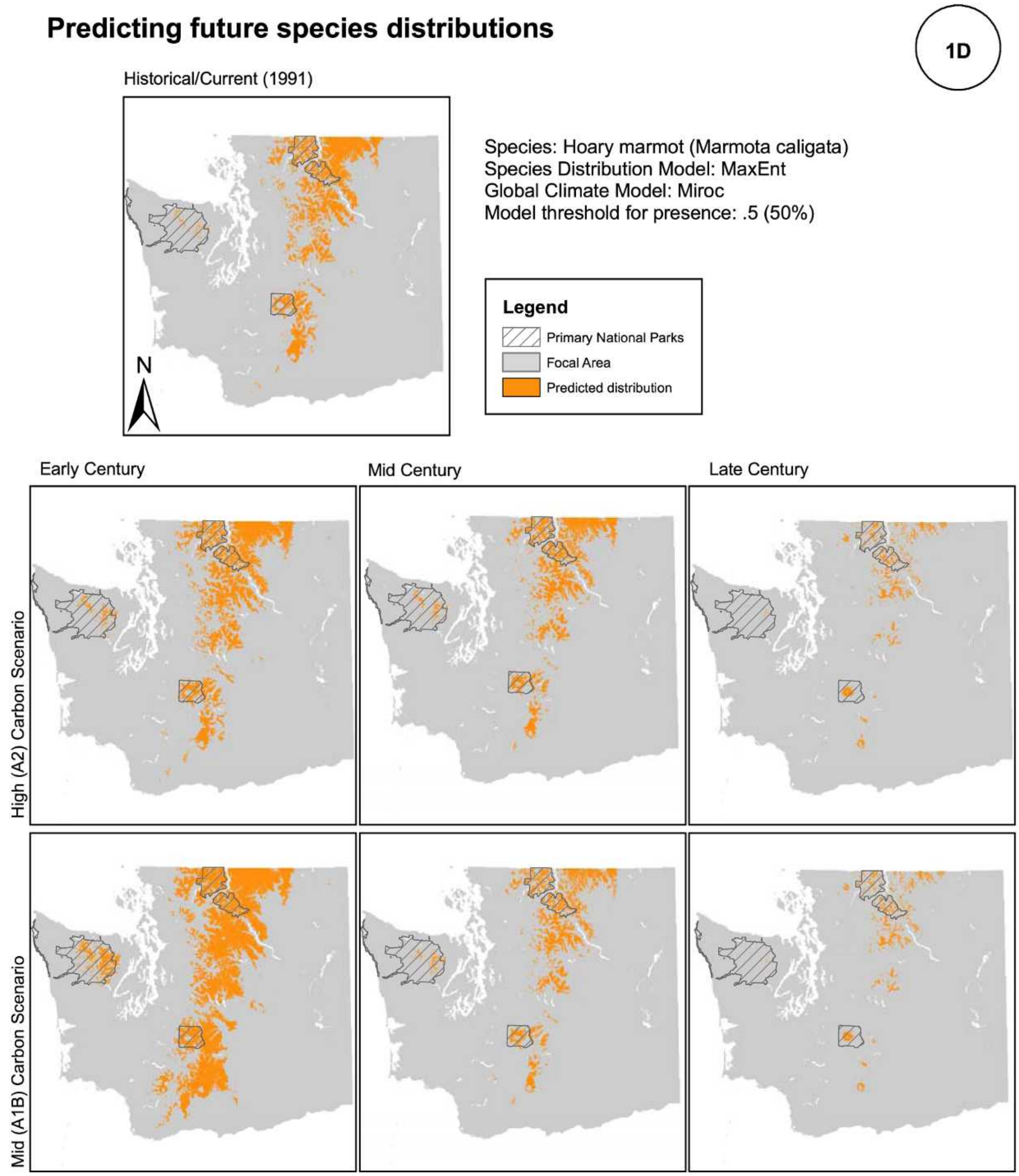
Results of species distribution modeling for eight montane mammal species using two different species distribution modeling approaches (logistic regression and maximum entropy [MaxEnt]), two climate model outputs (Hadley and Miroc), two IPCC carbon emissions scenarios and three future time periods (early: 2020–2024; mid: 2050–2054; late: 2095–2099) within the 21st century, giving a total of 32 sets of seven images. These are organized into four sets (A–D) for each

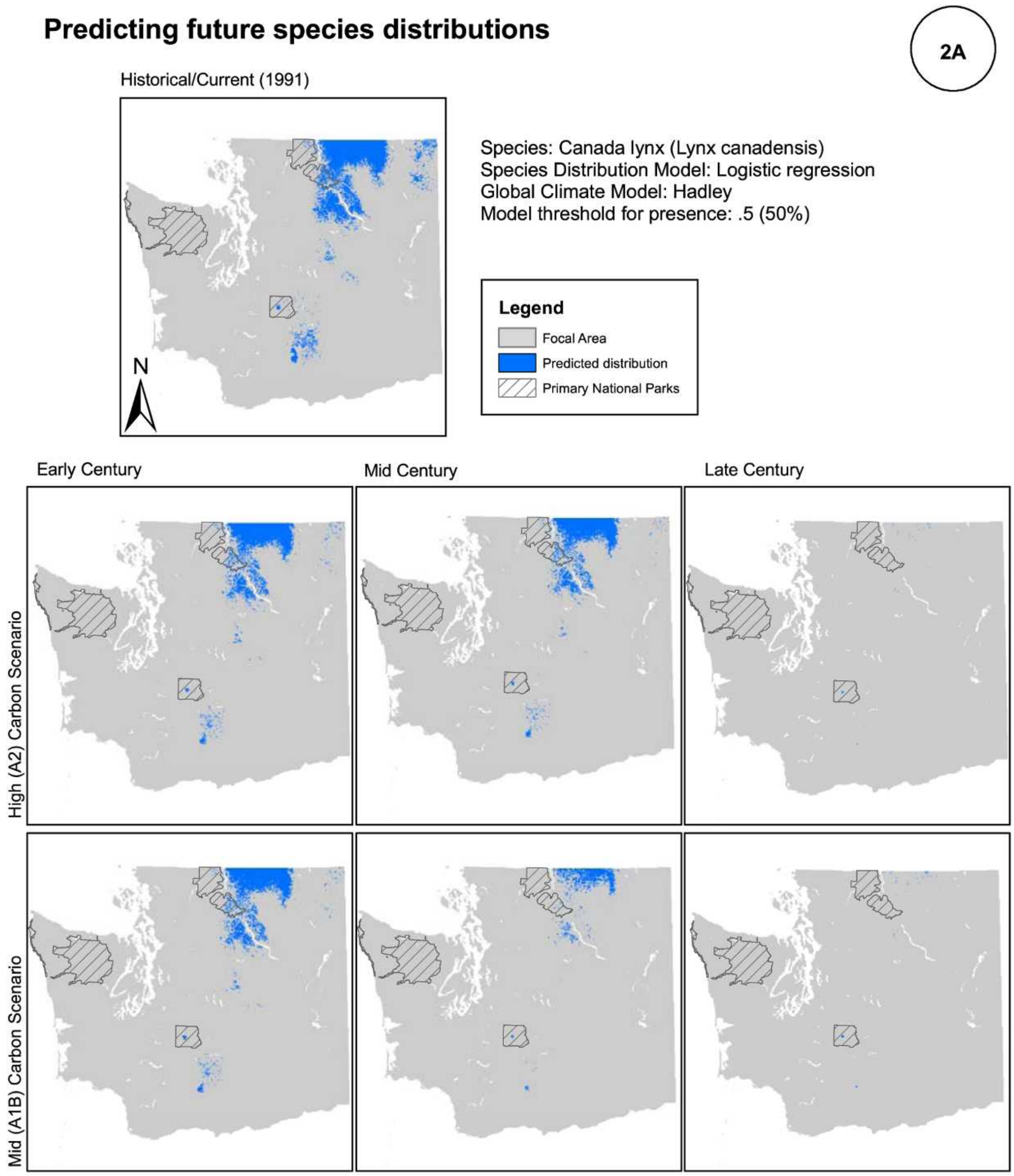


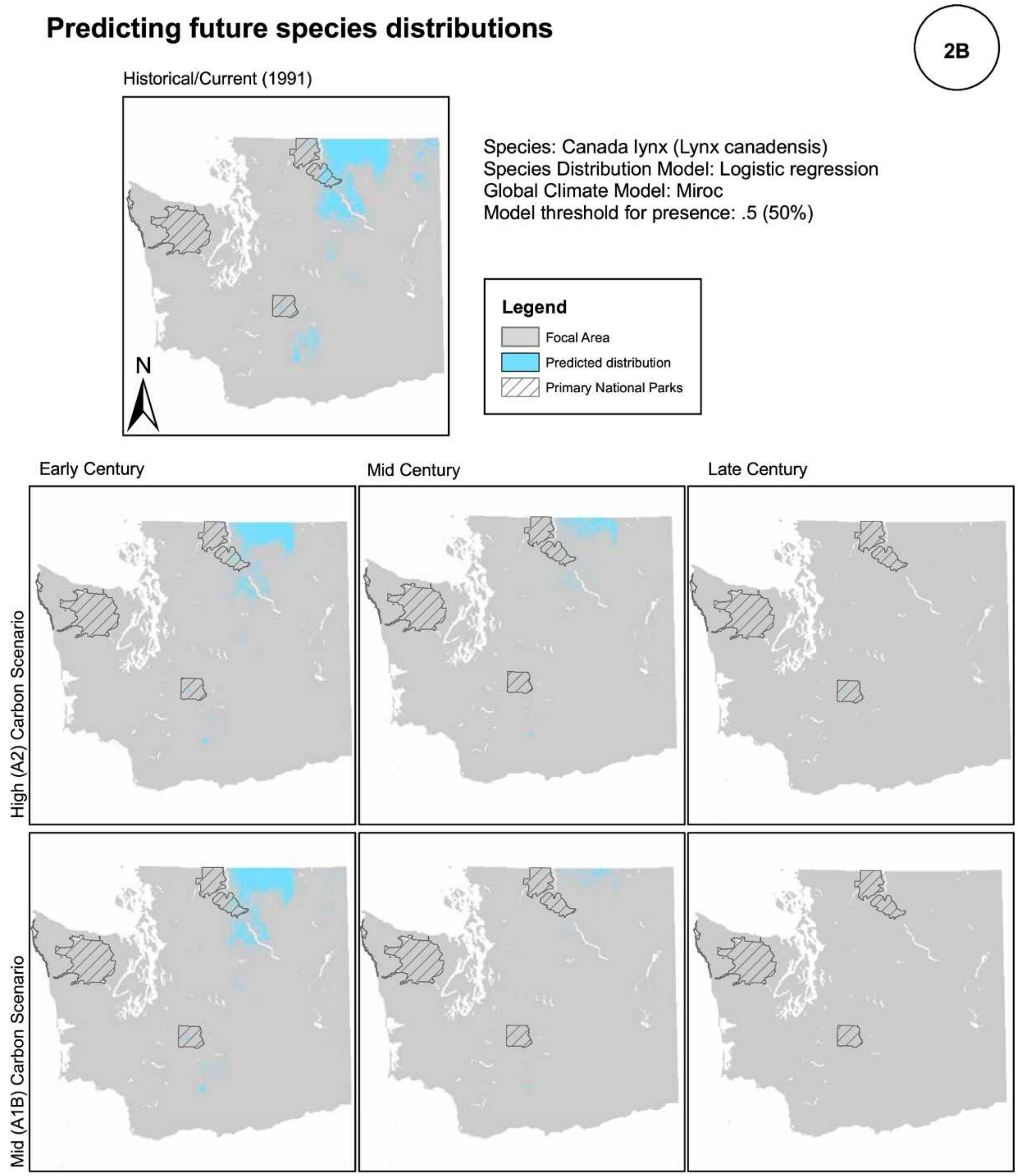
species (see letter and number combinations in upper right corner). Each of the four figures per species relate current species distribution and projected future distributions in light of model choice (logistic regression [A and B] vs. Maxent [C and D]), and climate change GCM scenario (Hadley [A and C] vs. Miroc [B and D]) on projections of future species distributions. Each figure depicts future outcomes for the two emissions scenarios and time periods and includes modeling and scenario information.

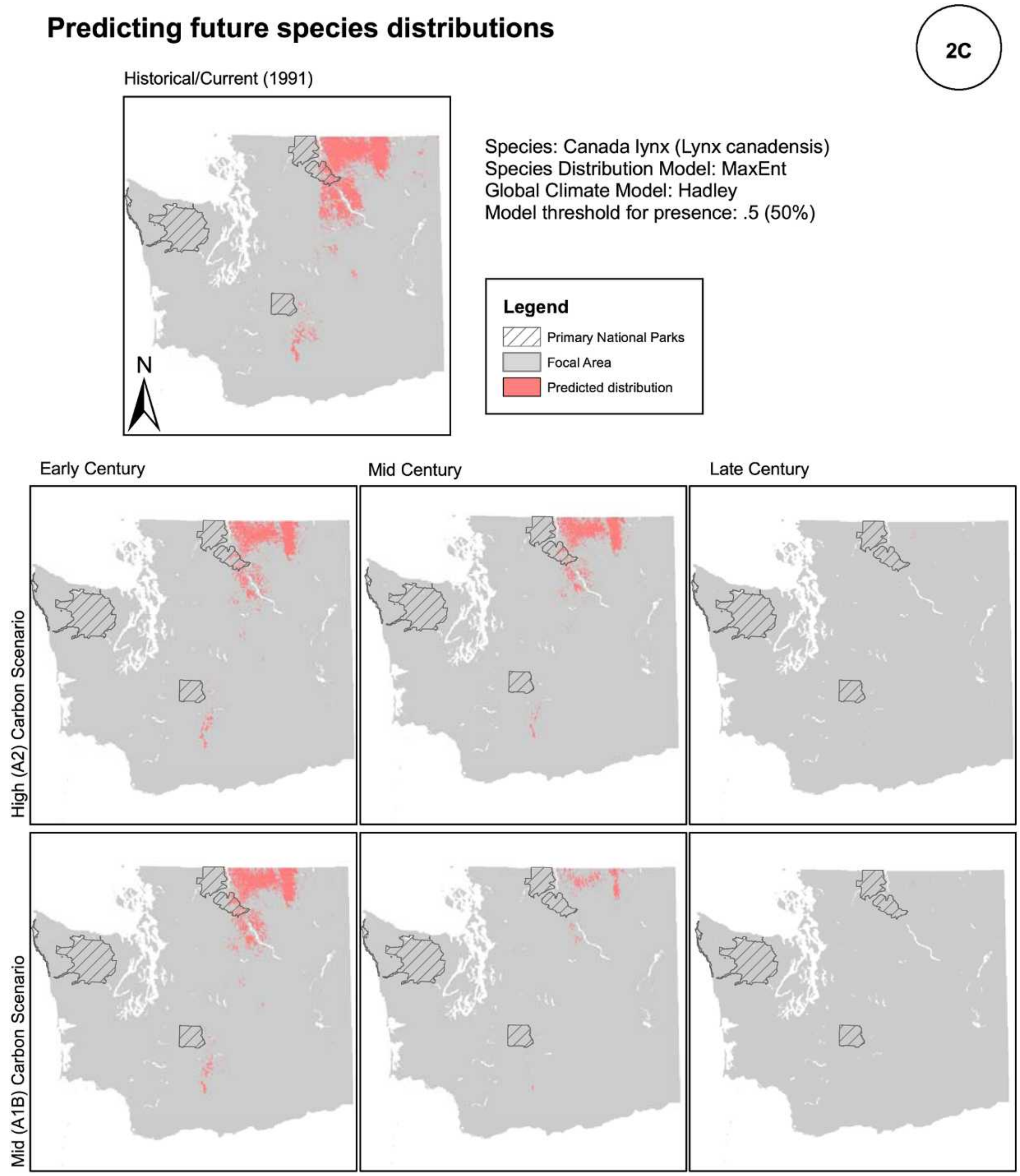


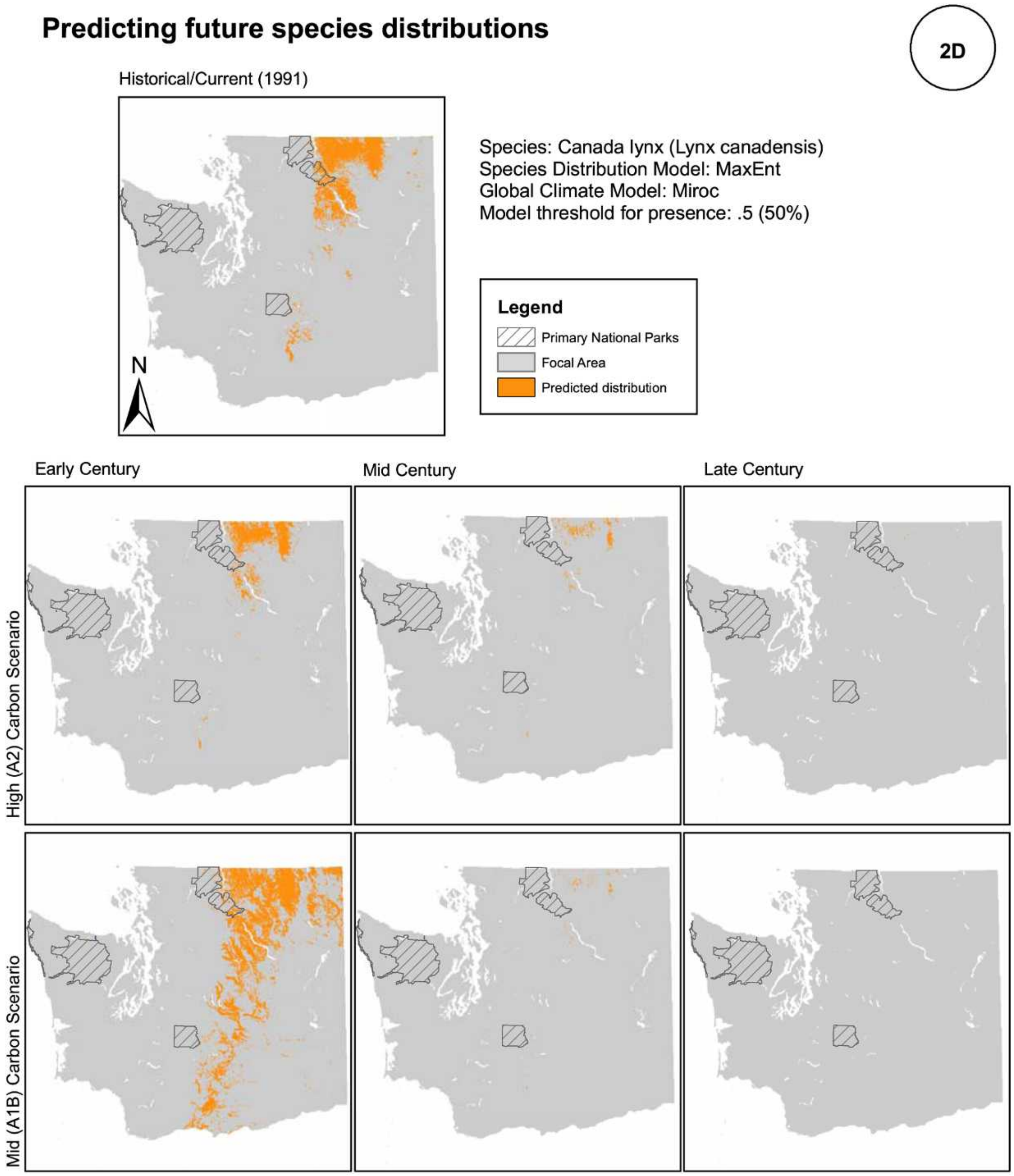

Predicting future species distributions
1C
Historical/Current (1991)
Species: Hoary marmot (Marmota caligata)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
1D
Historical/Current (1991)
Species: Hoary marmot (Marmota caligata)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

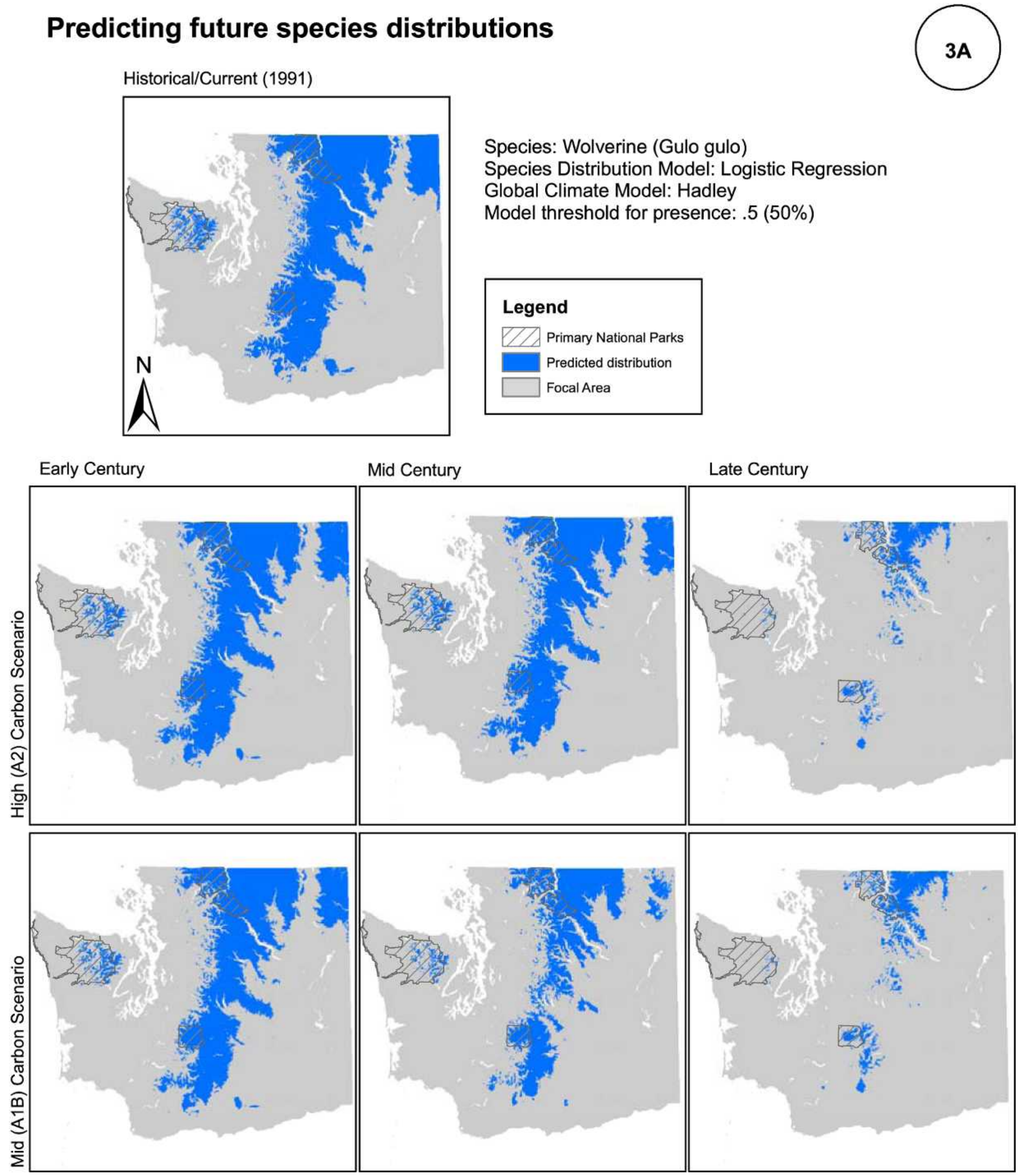

Predicting future species distributions
2A
Historical/Current (1991)
Species: Canada lynx (Lynx canadensis)
Species Distribution Model: Logistic regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

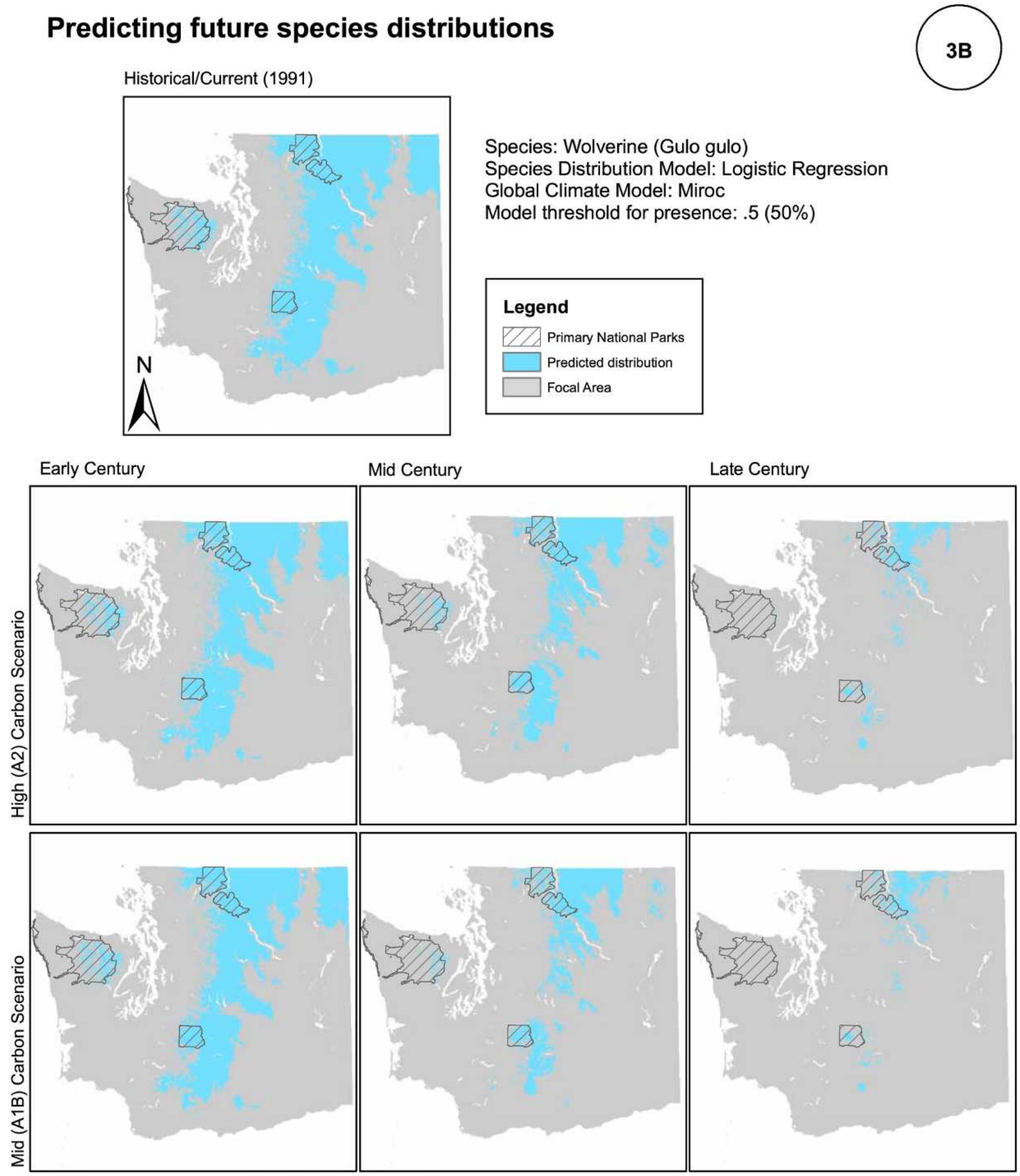

Predicting future species distributions
2B
Historical/Current (1991)
Species: Canada lynx (Lynx canadensis)
Species Distribution Model: Logistic regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

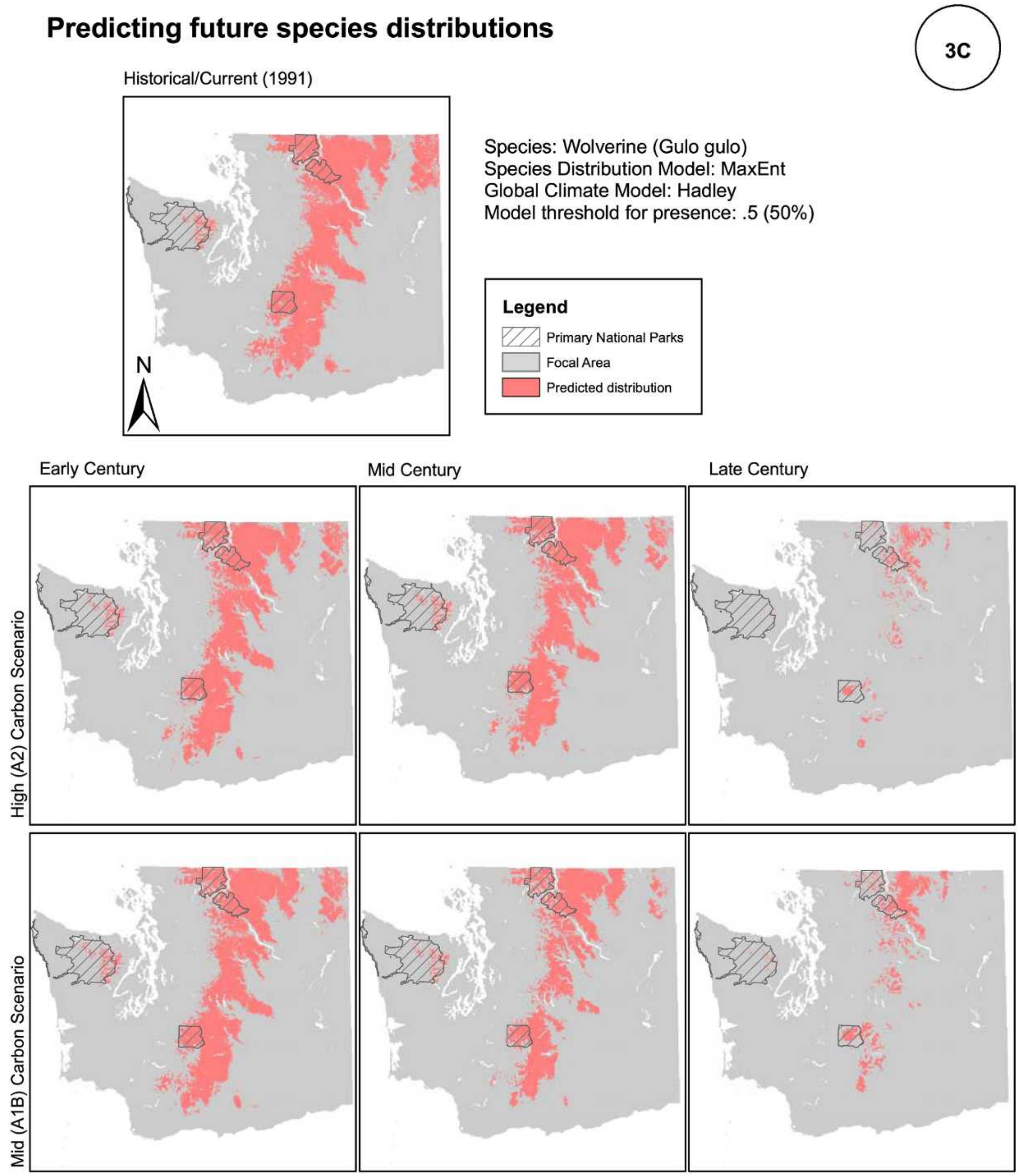

Predicting future species distributions
2C
Historical/Current (1991)
Species: Canada lynx (Lynx canadensis)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

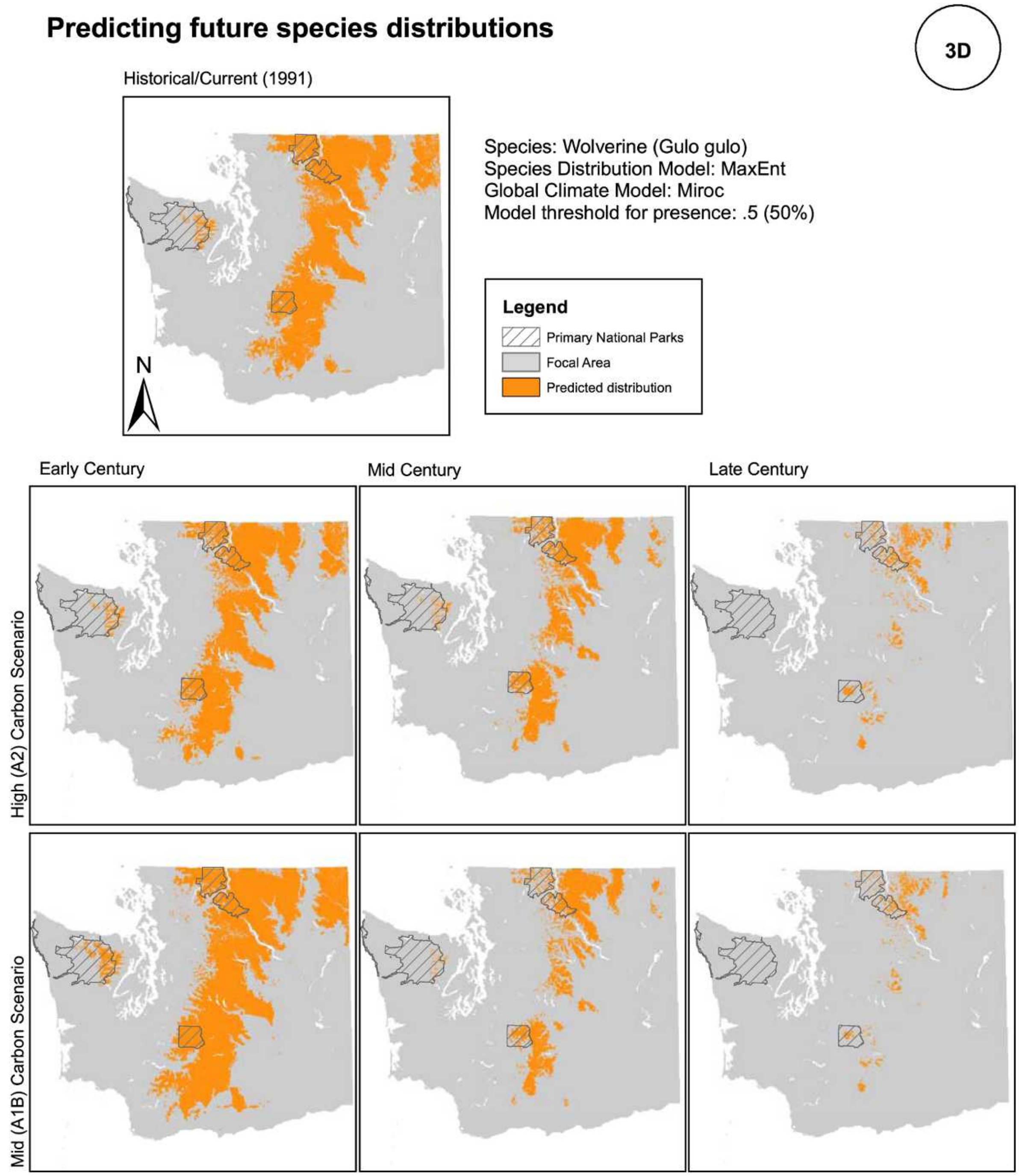


Predicting future species distributions
2D
Historical/Current (1991)
Species: Canada lynx (Lynx canadensis)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

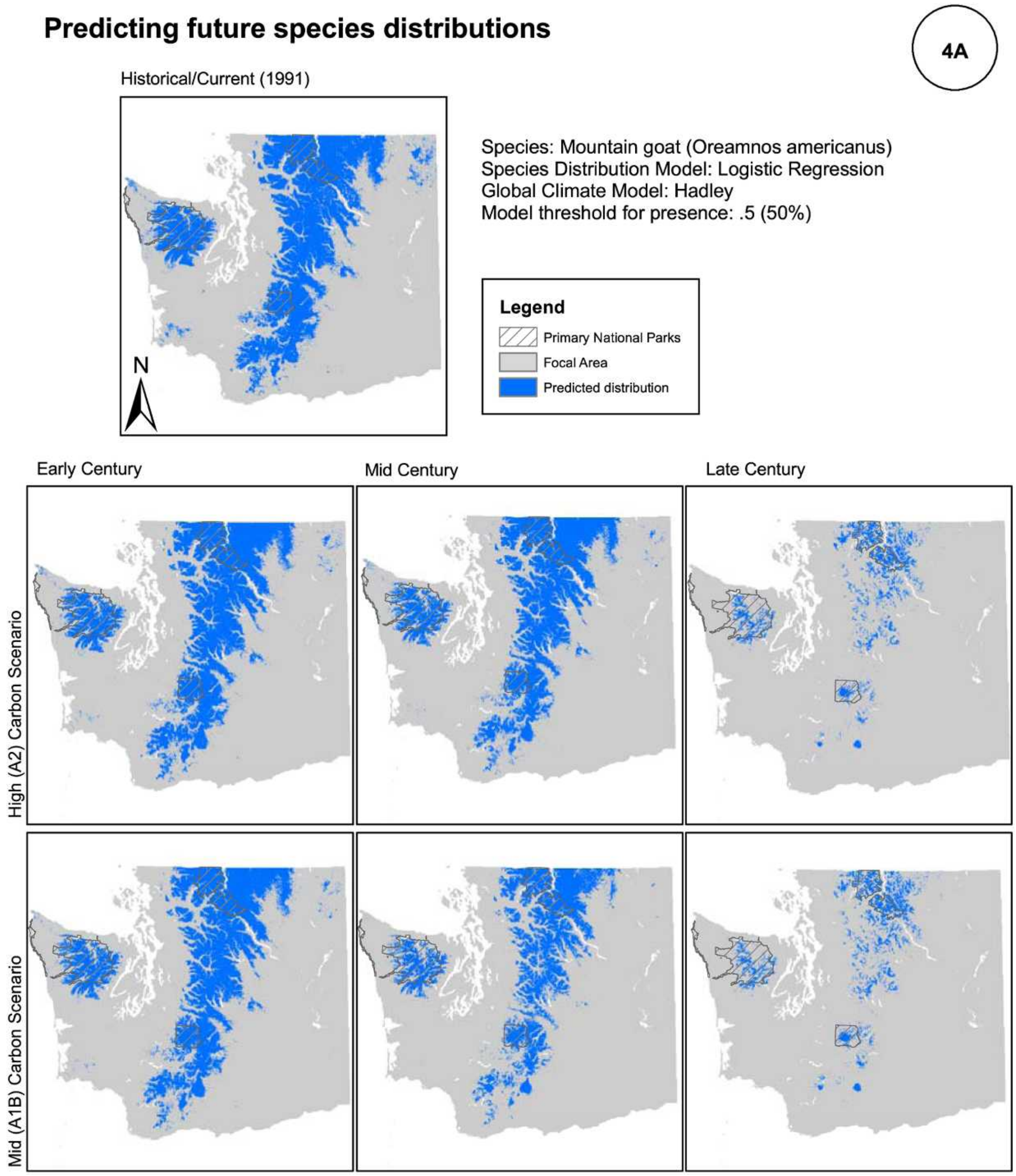

Predicting future species distributions
3A
Historical/Current (1991)
N
Species: Wolverine (Gulo gulo)
Species Distribution Model: Logistic Regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Predicted distribution
Focal Area
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

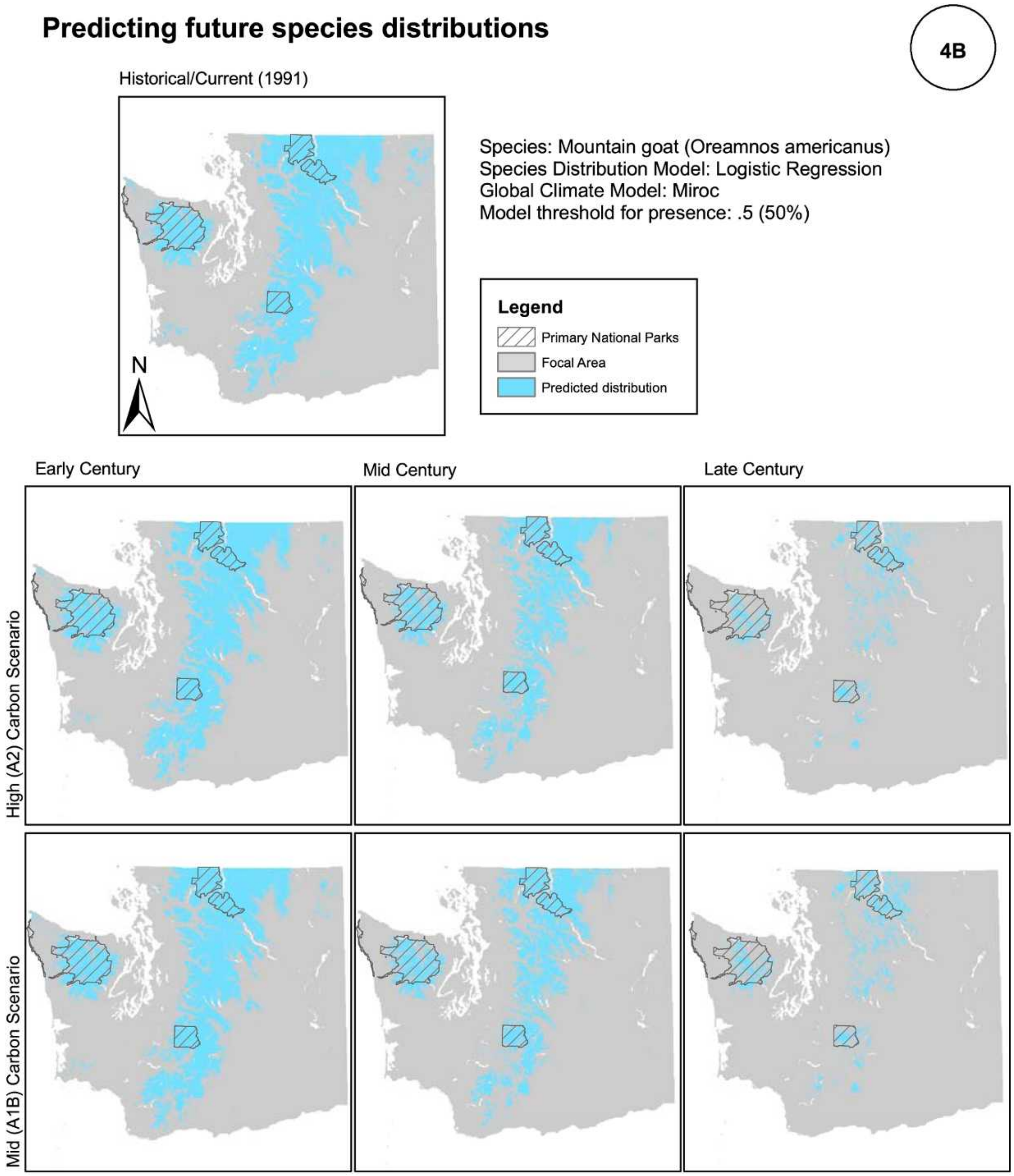

Predicting future species distributions
3B
Historical/Current (1991)
Species: Wolverine (Gulo gulo)
Species Distribution Model: Logistic Regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Predicted distribution
Focal Area
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

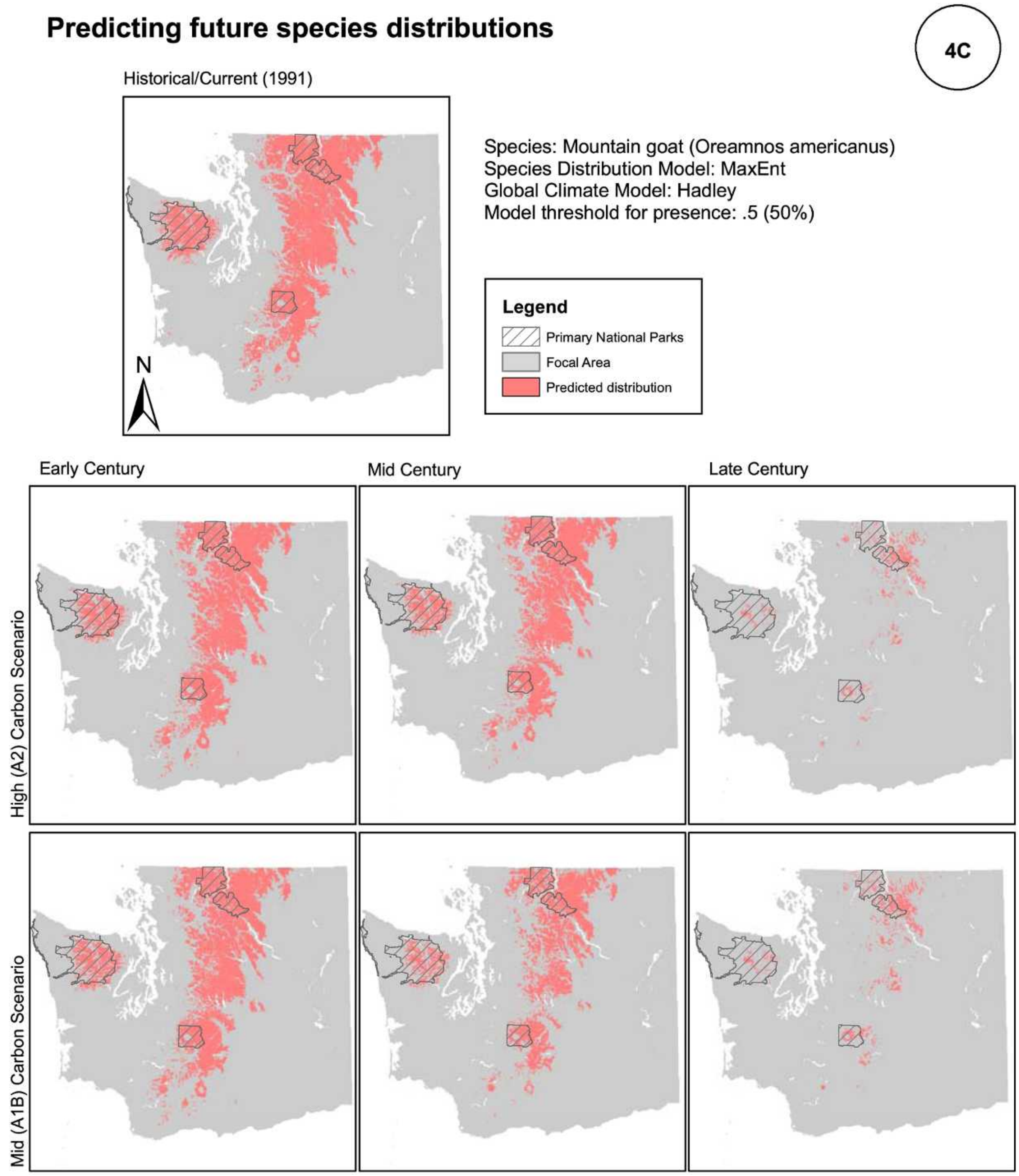

Predicting future species distributions
3C
Historical/Current (1991)
N
Species: Wolverine (Gulo gulo)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

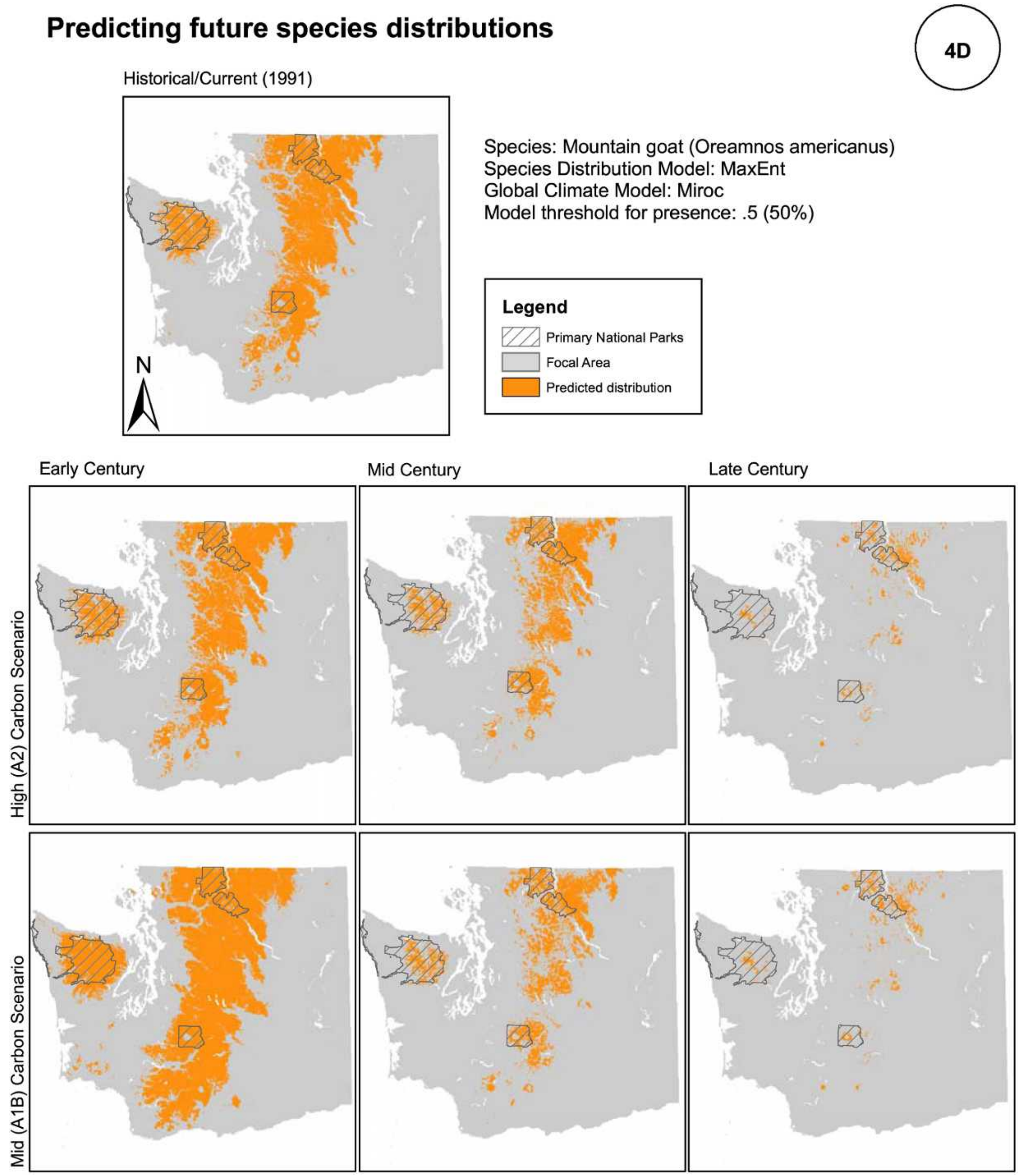


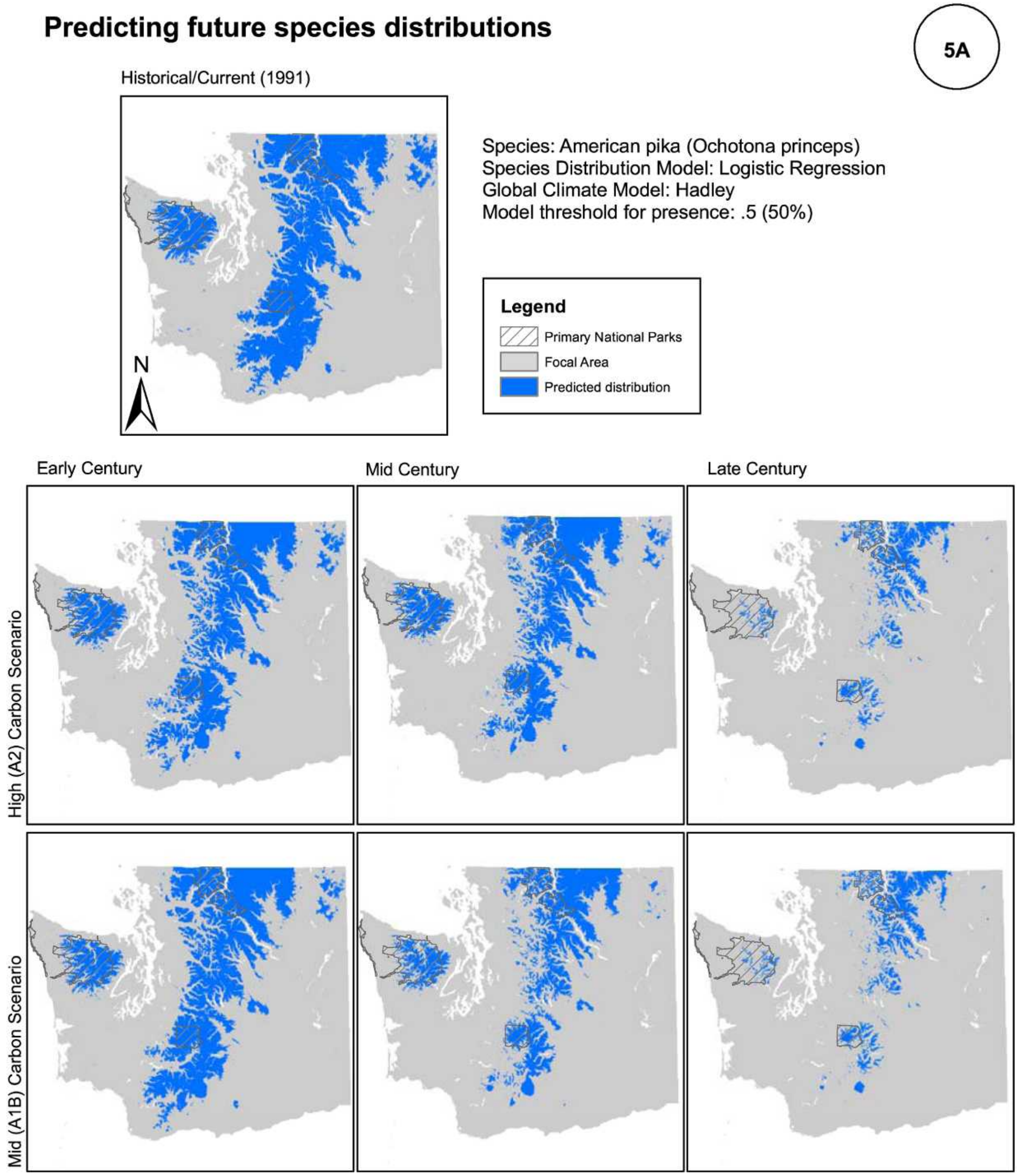
Predicting future species distributions
3D
Historical/Current (1991)
Species: Wolverine (Gulo gulo)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

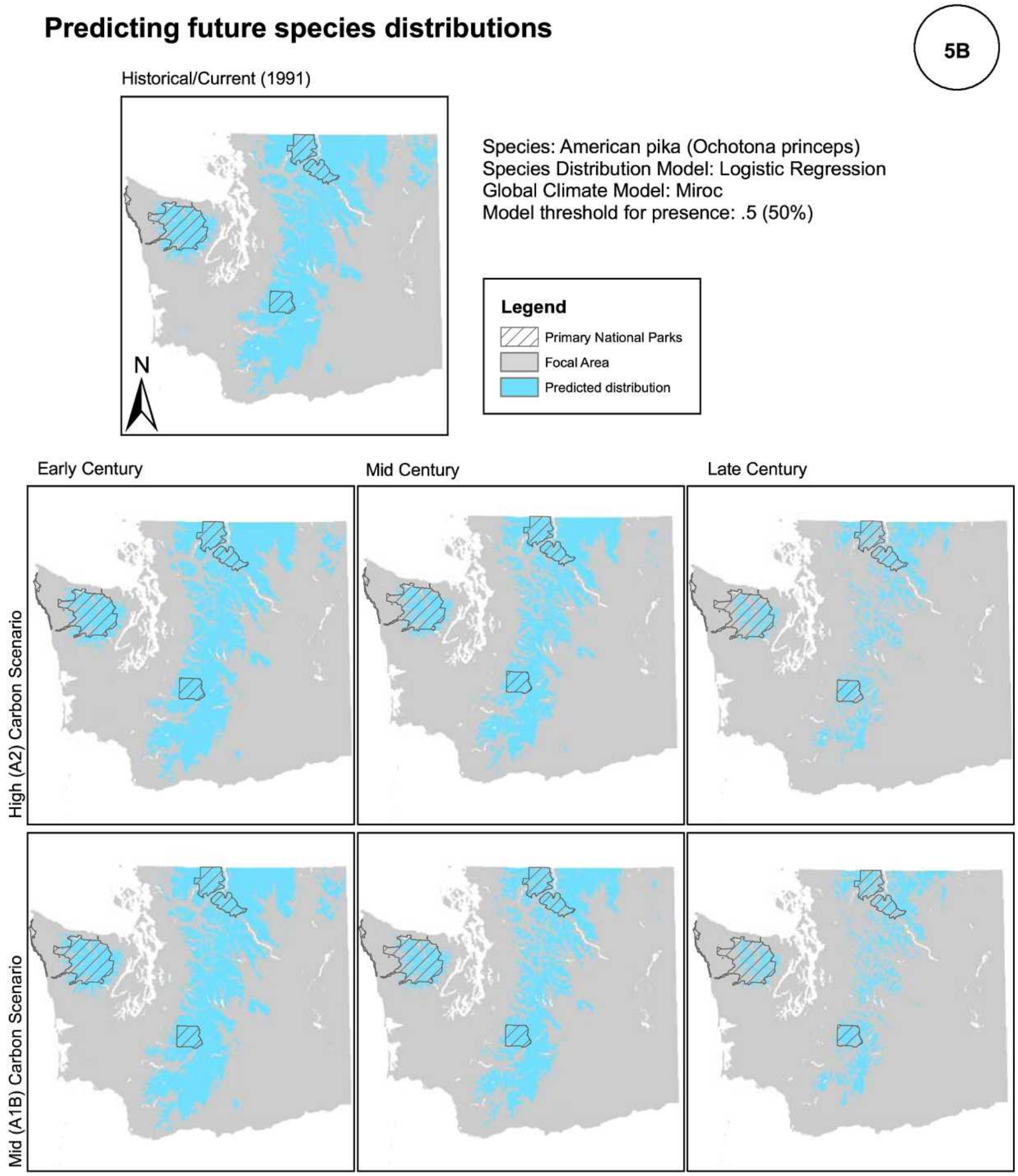

Predicting future species distributions
4A
Historical/Current (1991)
Species: Mountain goat (Oreamnos americanus)
Species Distribution Model: Logistic Regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

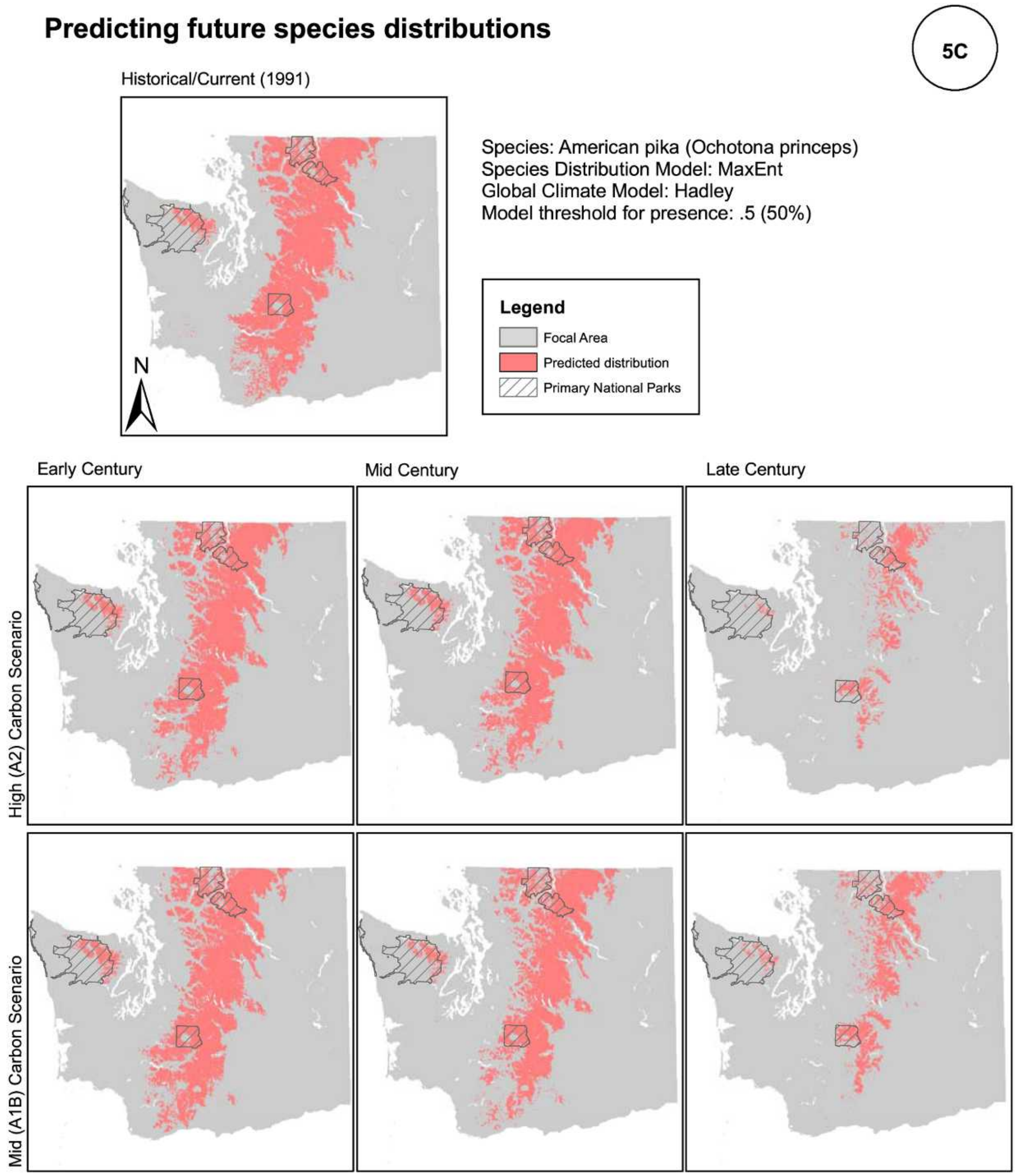

Predicting future species distributions
4B
Historical/Current (1991)
Species: Mountain goat (Oreamnos americanus)
Species Distribution Model: Logistic Regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

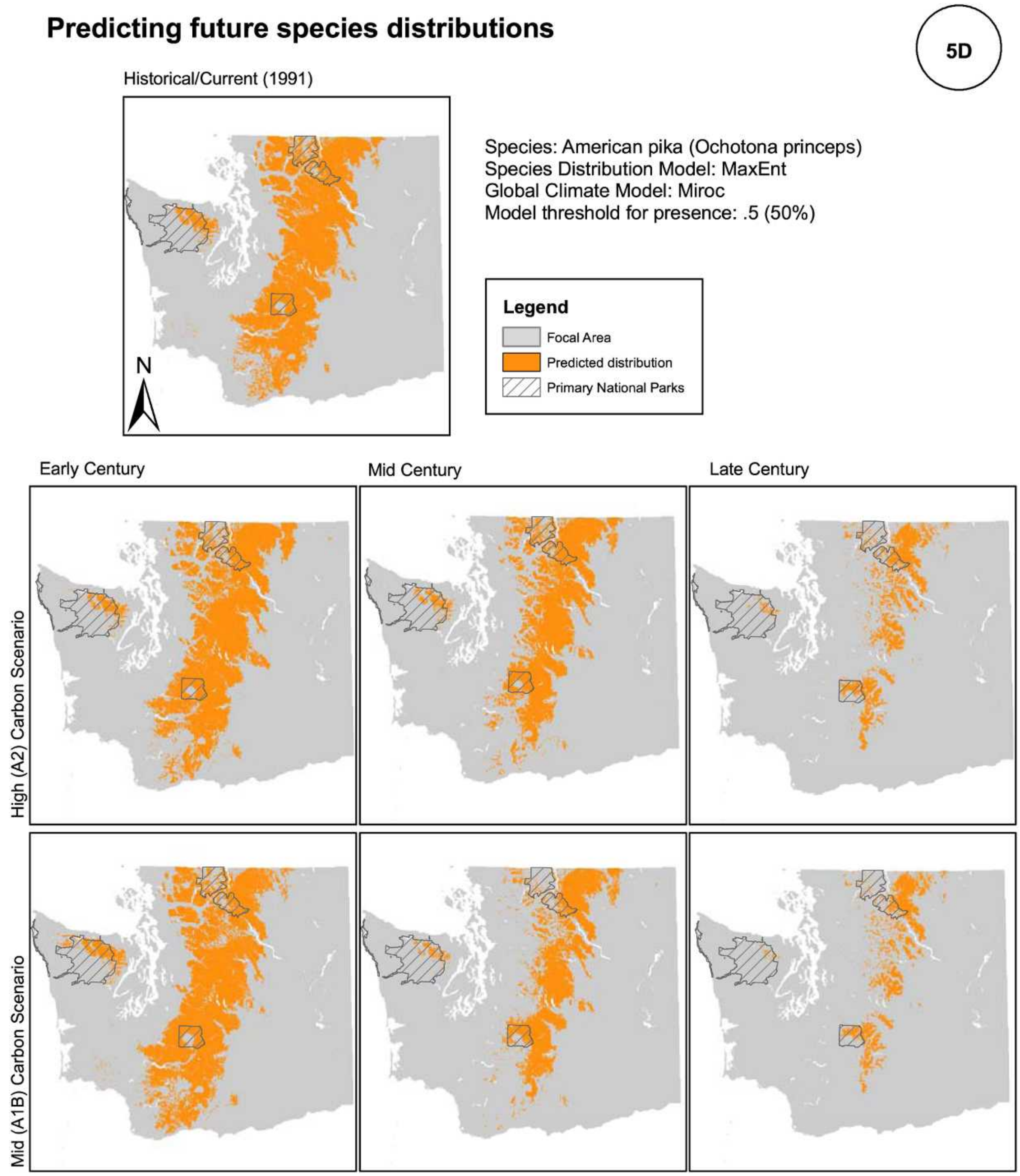

Predicting future species distributions
4C
Historical/Current (1991)
N
Species: Mountain goat (Oreamnos americanus)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

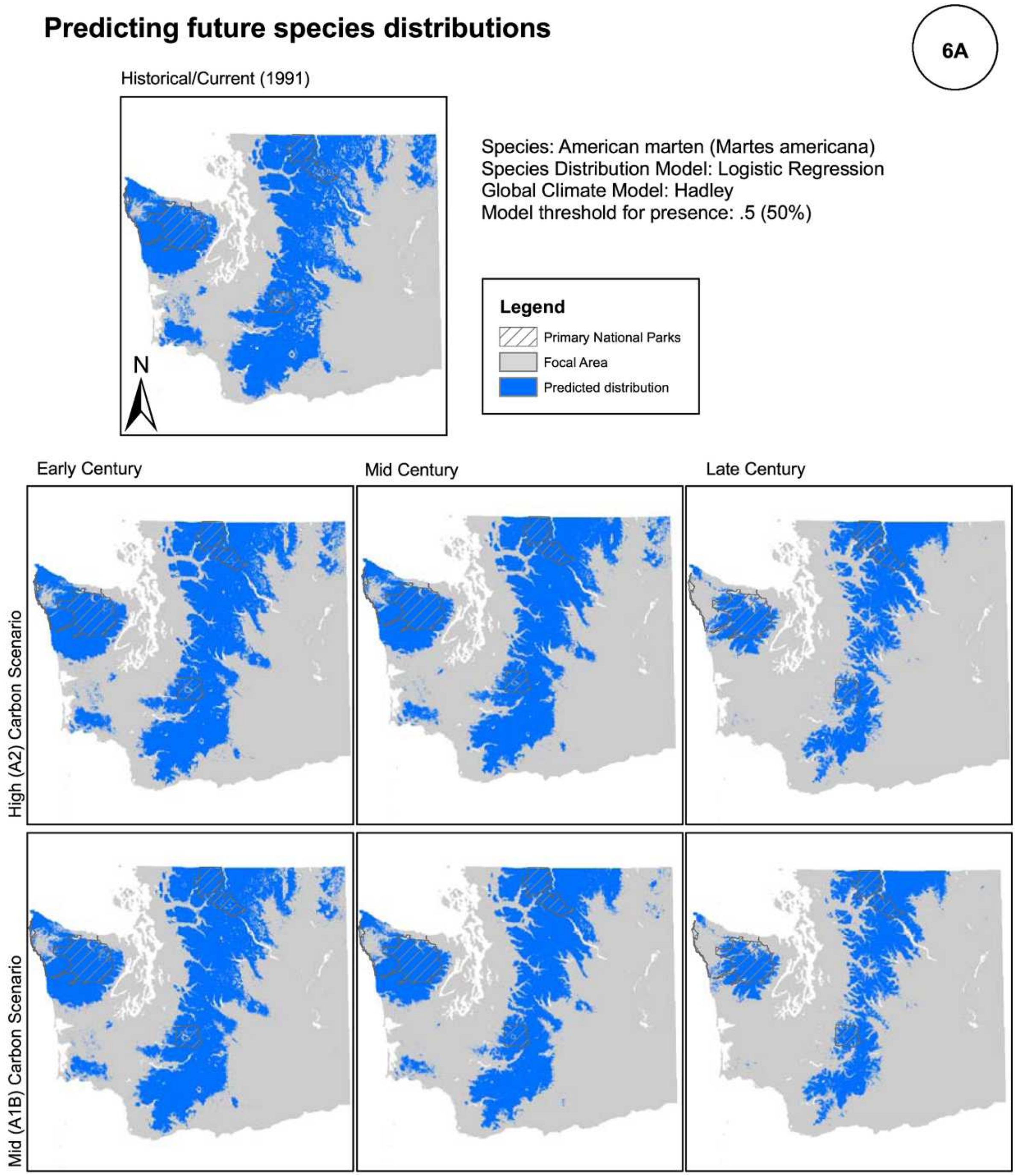

Predicting future species distributions
4D
Historical/Current (1991)
Species: Mountain goat (Oreamnos americanus)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

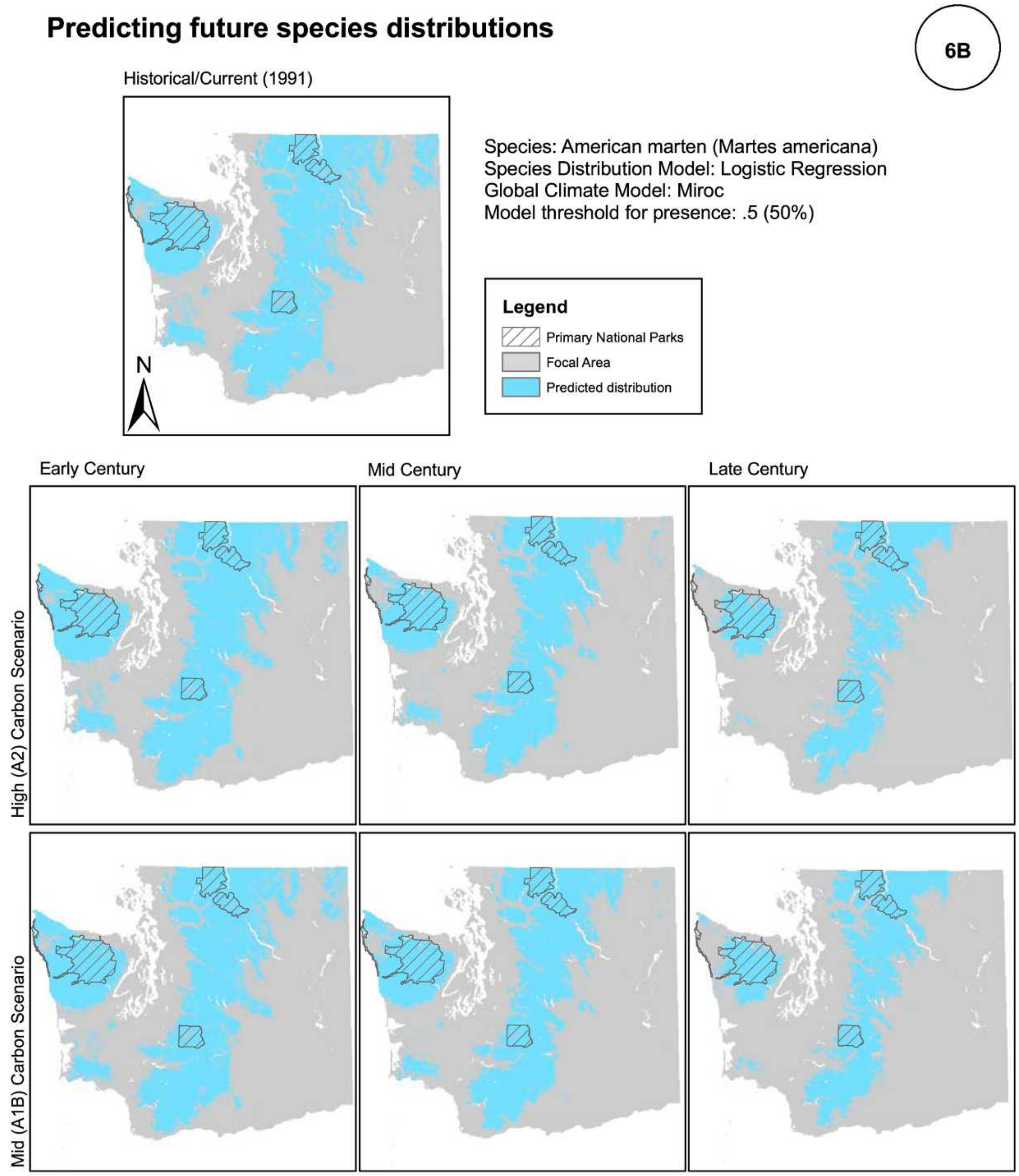

Predicting future species distributions
5A
Historical/Current (1991)
Species: American pika (Ochotona princeps)
Species Distribution Model: Logistic Regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

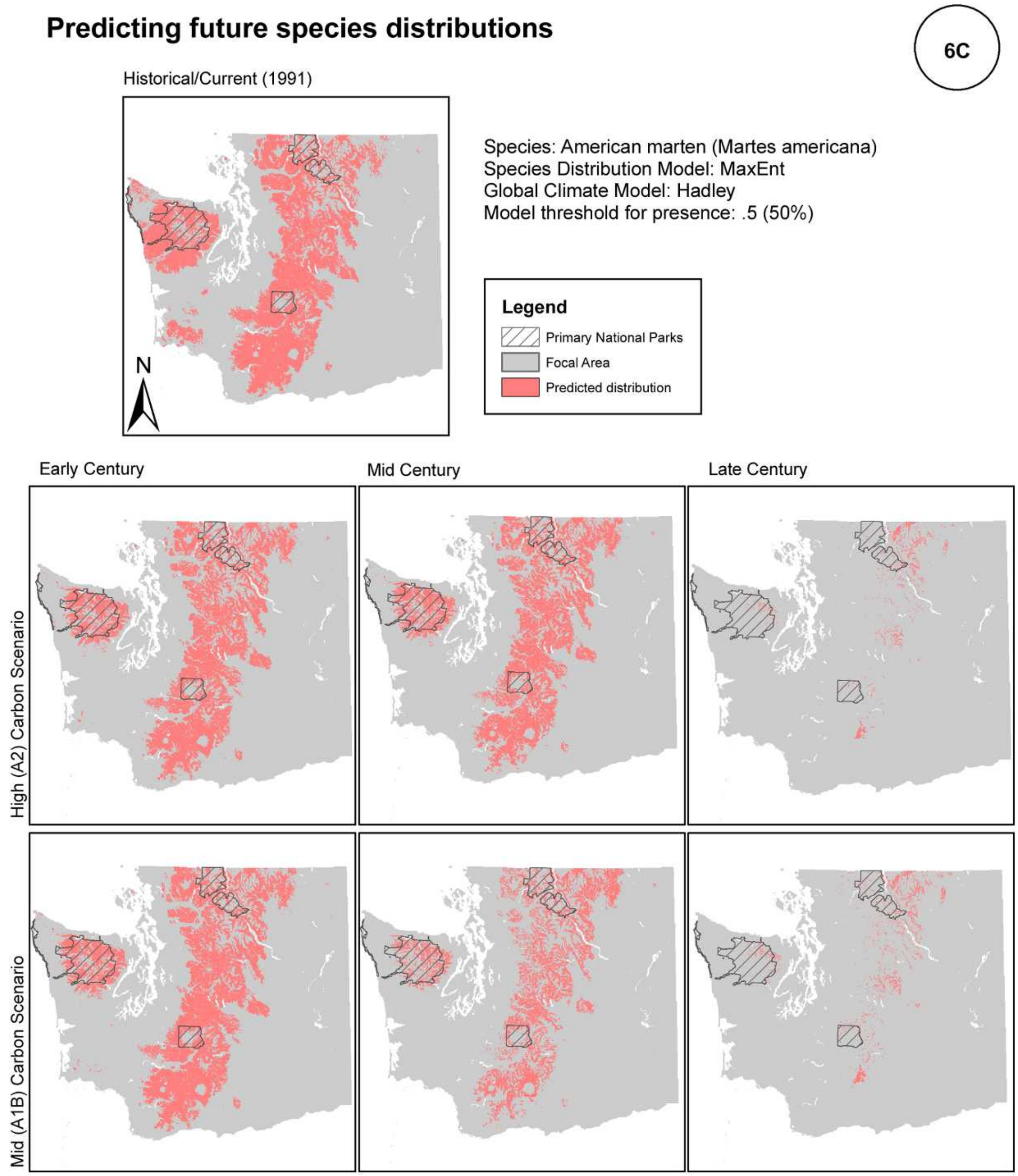

Predicting future species distributions
5B
Historical/Current (1991)
Species: American pika (Ochotona princeps)
Species Distribution Model: Logistic Regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
5C
Historical/Current (1991)
Species: American pika (Ochotona princeps)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

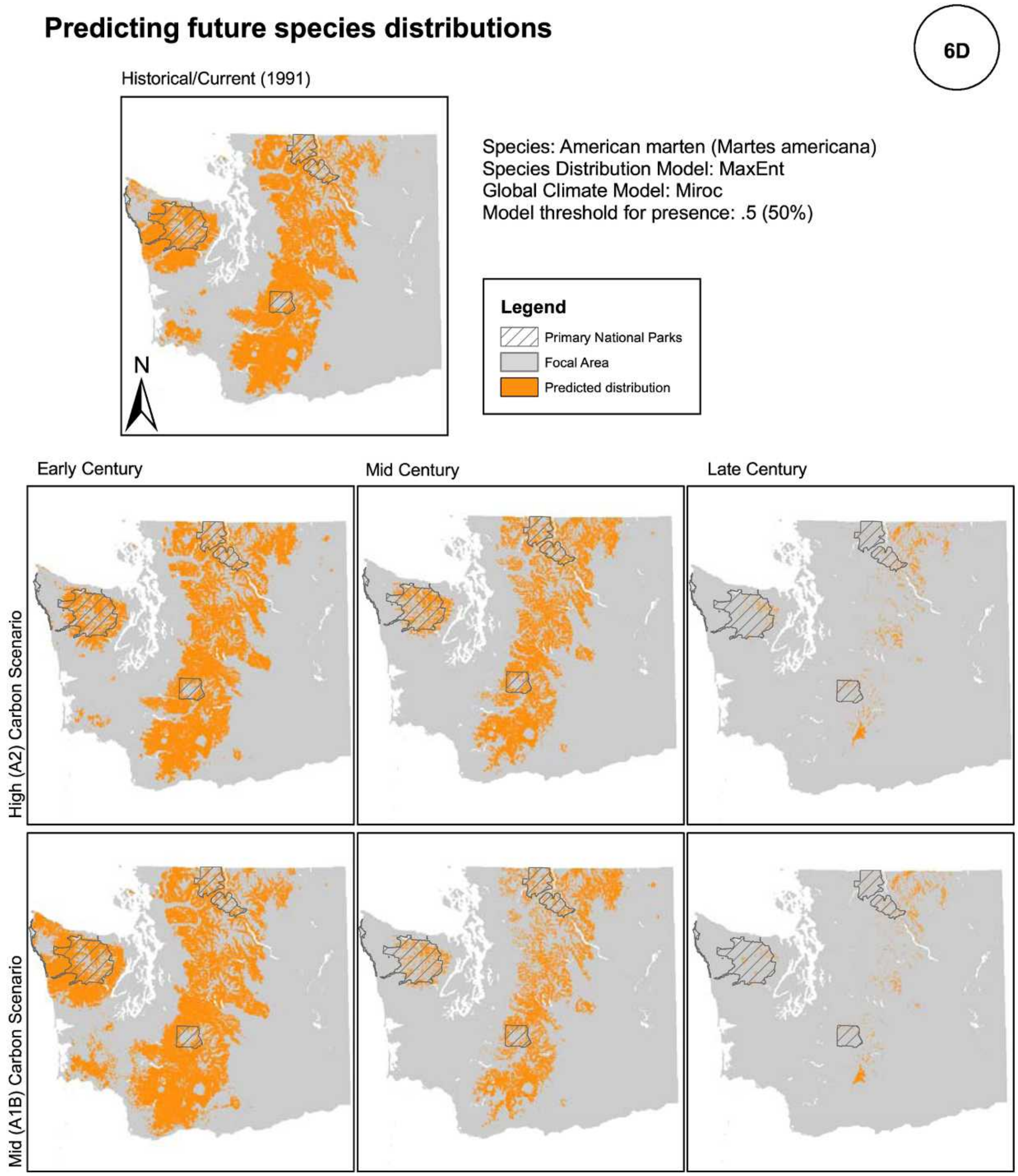

Predicting future species distributions
5D
Historical/Current (1991)
Species: American pika (Ochotona princeps)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

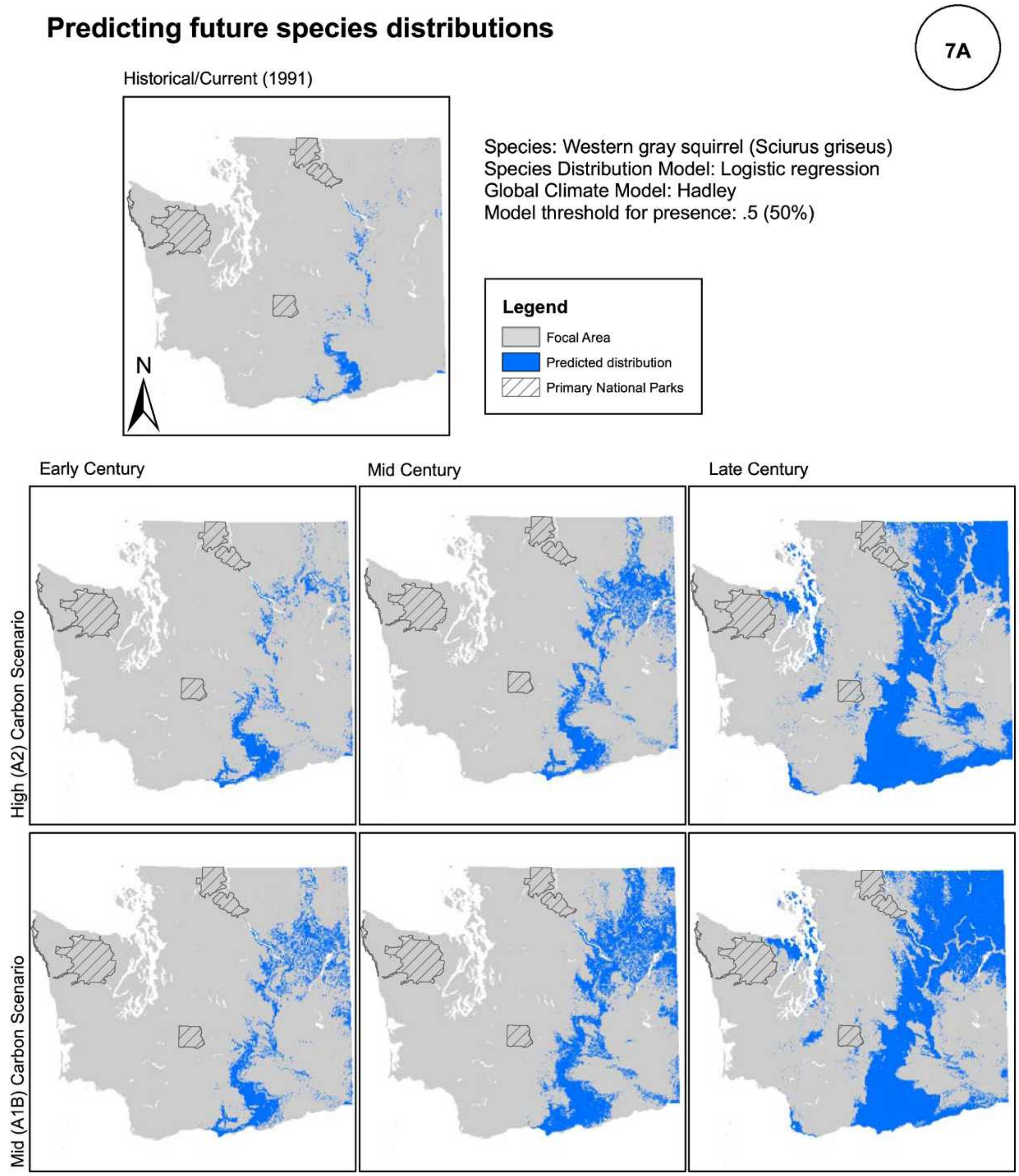

Predicting future species distributions
6A
Historical/Current (1991)
Species: American marten (Martes americana)
Species Distribution Model: Logistic Regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
6B
Historical/Current (1991)
N
Species: American marten (Martes americana)
Species Distribution Model: Logistic Regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

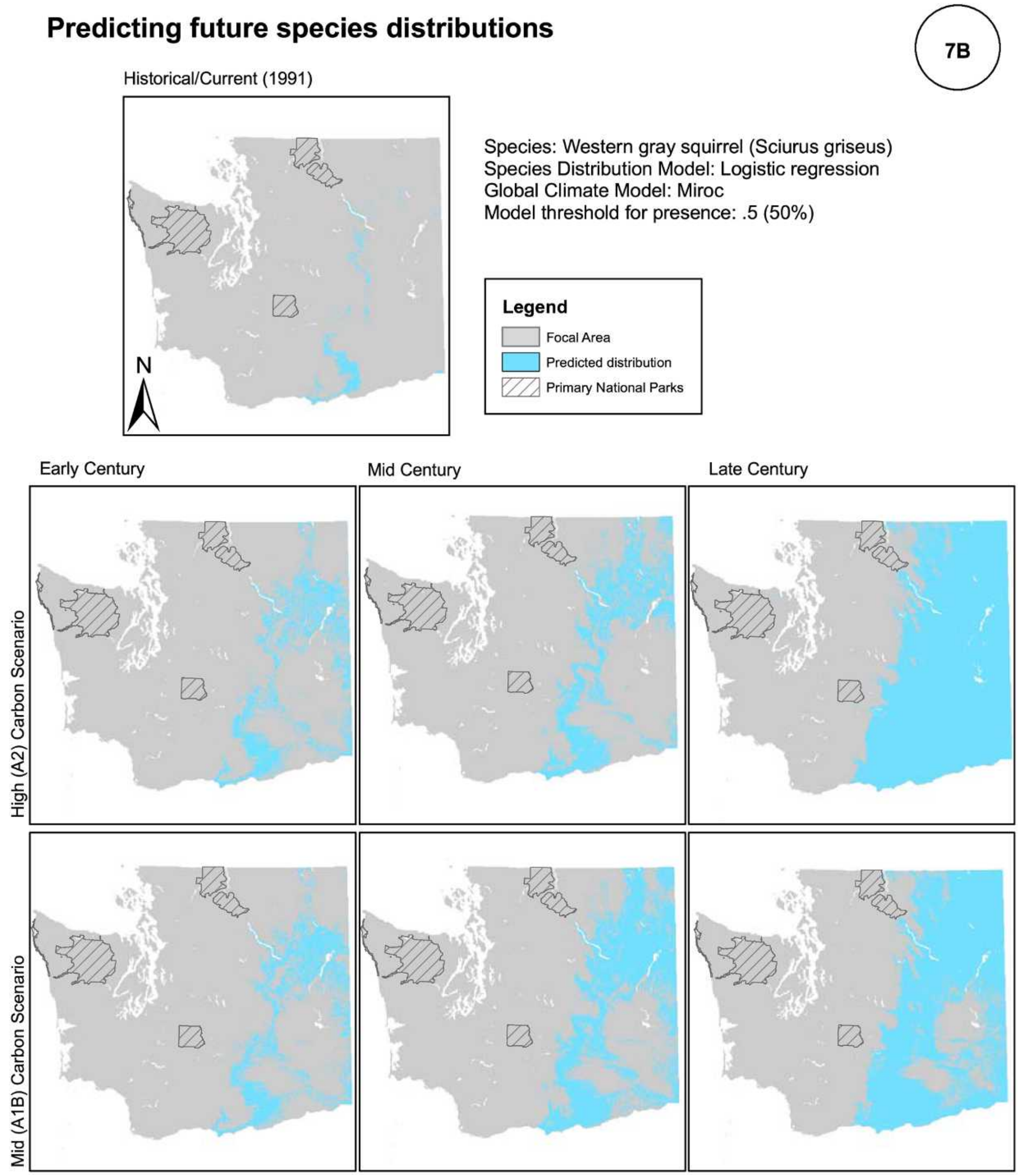


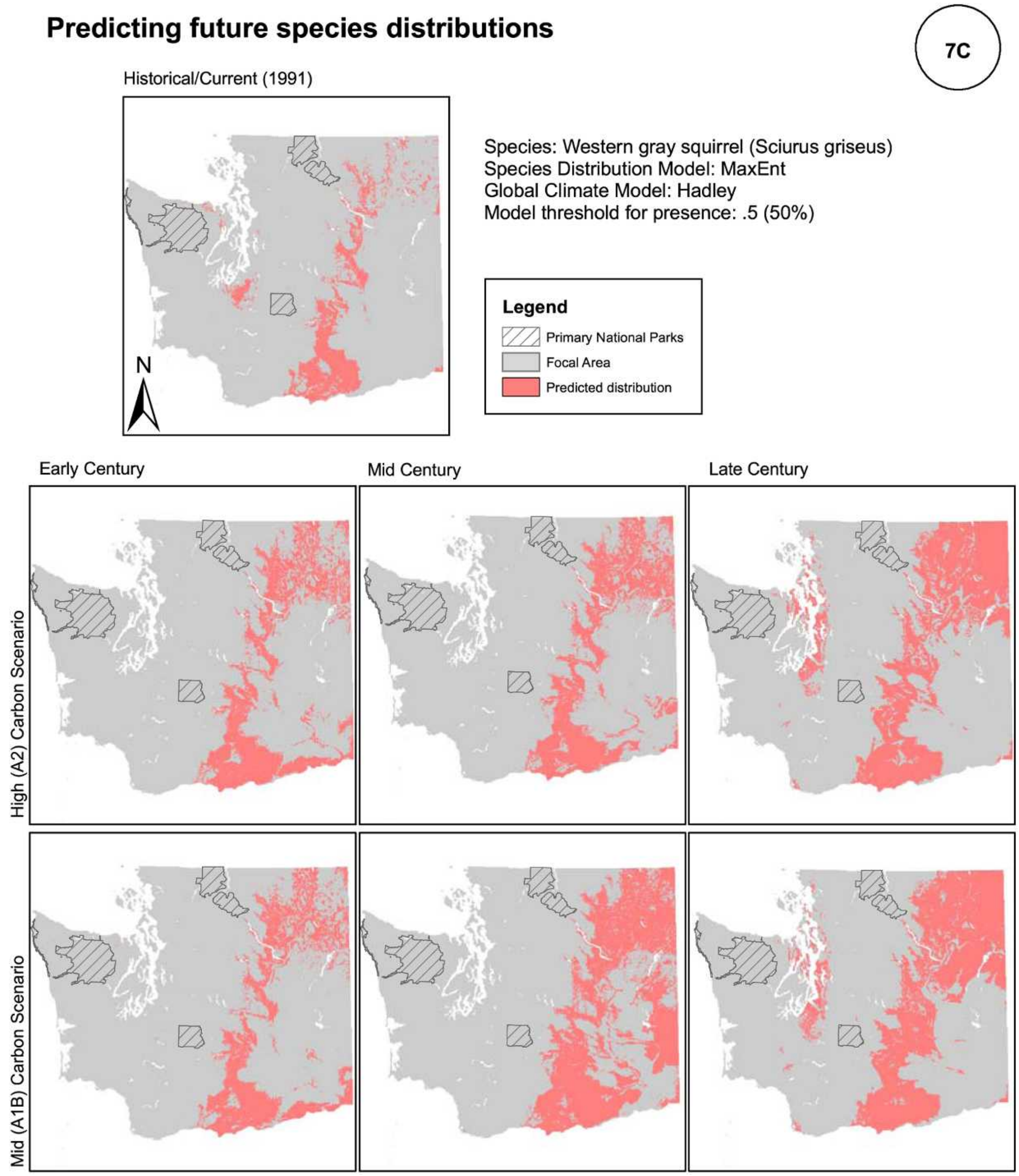
Predicting future species distributions
6C
Historical/Current (1991)
Species: American marten (Martes americana)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

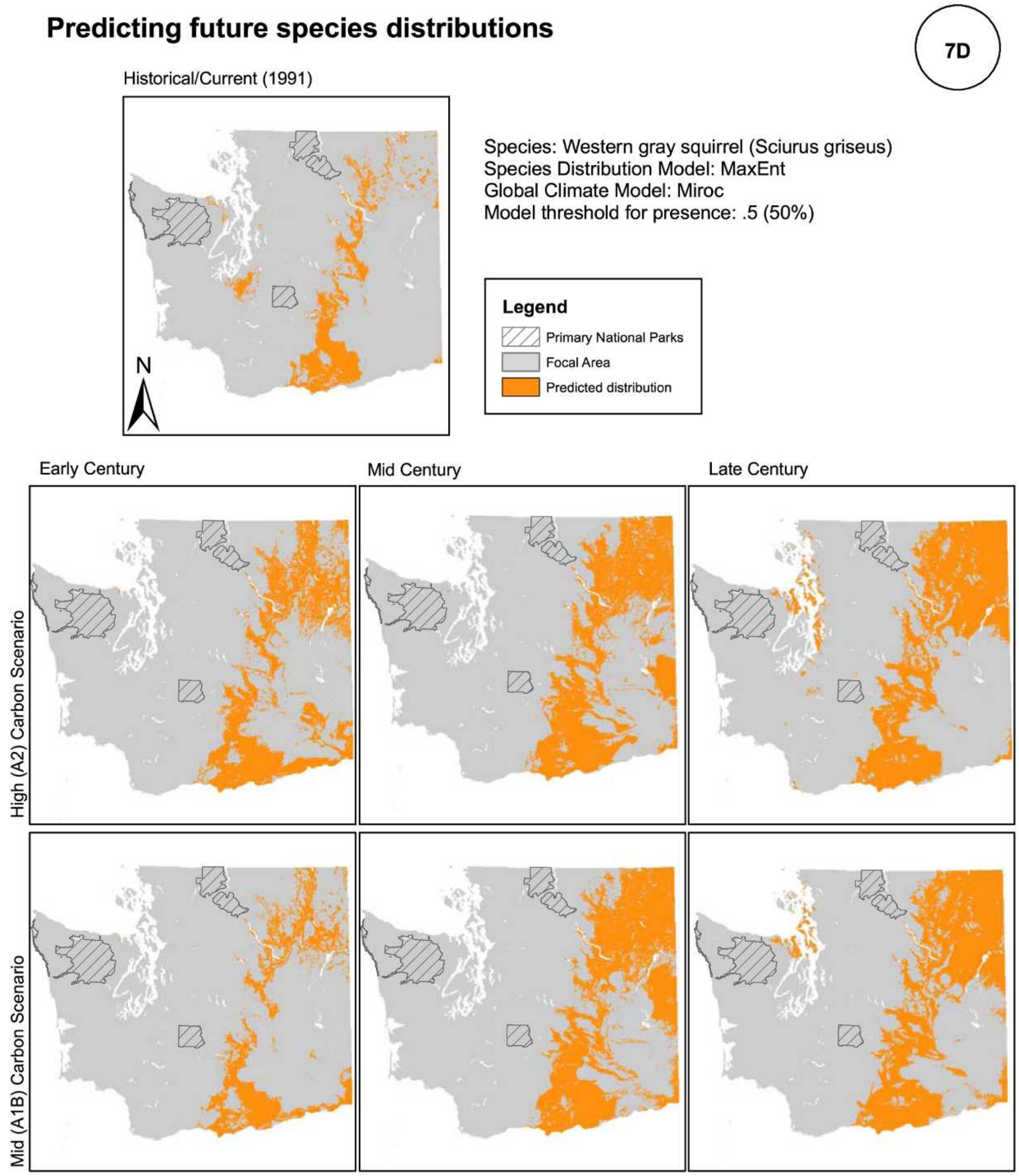

Predicting future species distributions
6D
Historical/Current (1991)
N
Species: American marten (Martes americana)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

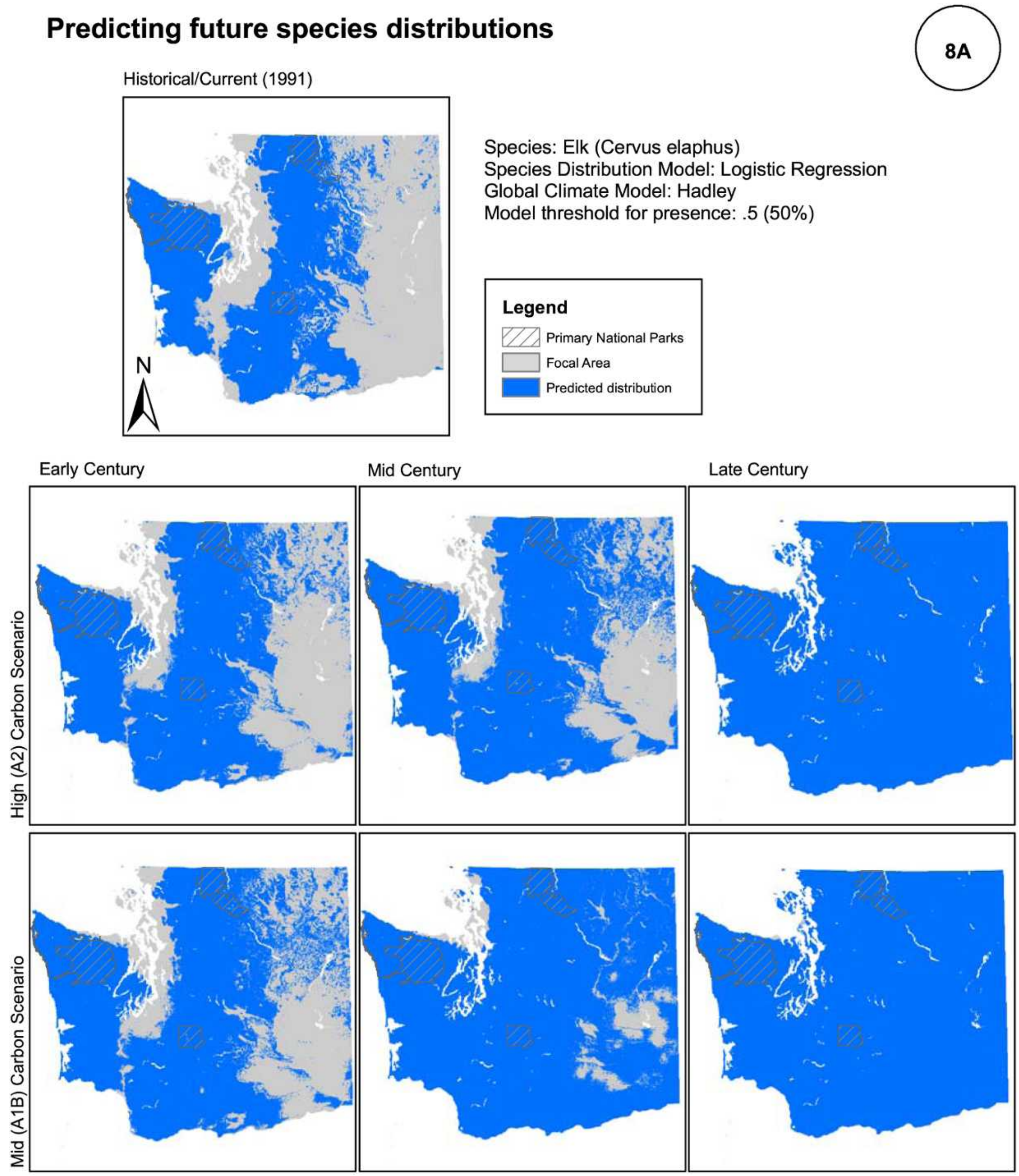


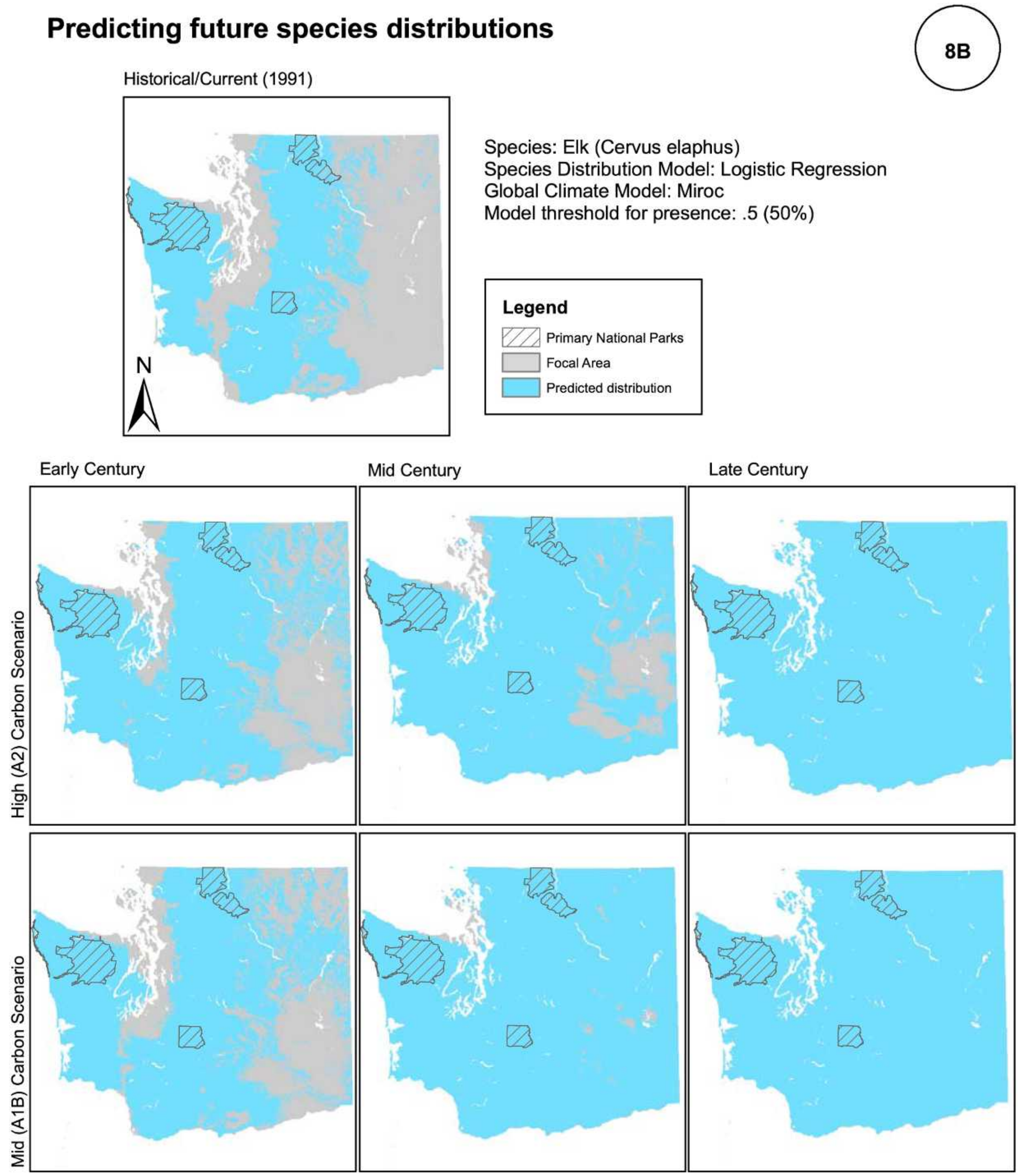
Predicting future species distributions
7A
Historical/Current (1991)
Species: Western gray squirrel (Sciurus griseus)
Species Distribution Model: Logistic regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

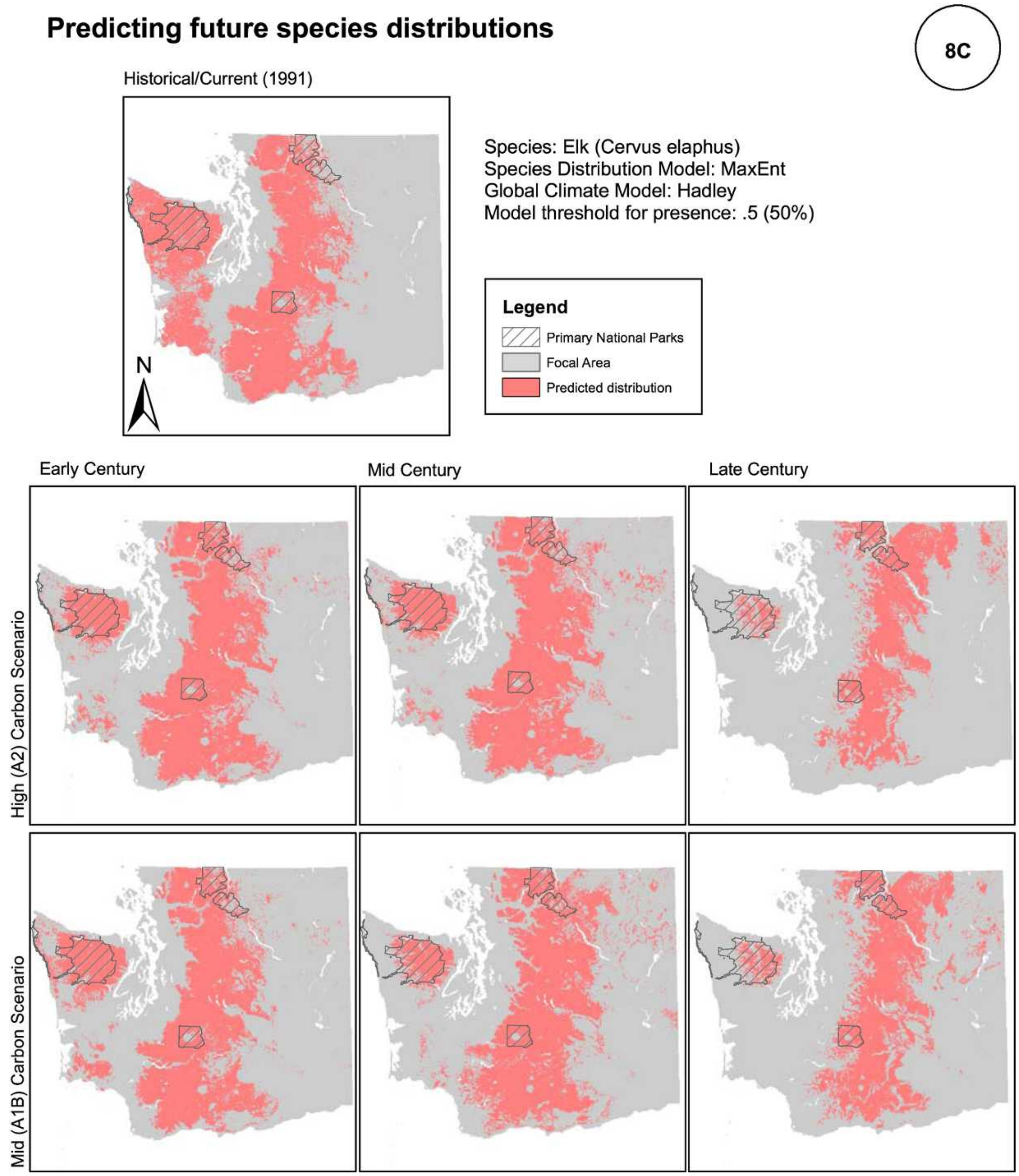

Predicting future species distributions
7B
Historical/Current (1991)
N
Species: Western gray squirrel (Sciurus griseus)
Species Distribution Model: Logistic regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Focal Area
Predicted distribution
Primary National Parks
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
7C
Historical/Current (1991)
Species: Western gray squirrel (Sciurus griseus)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario

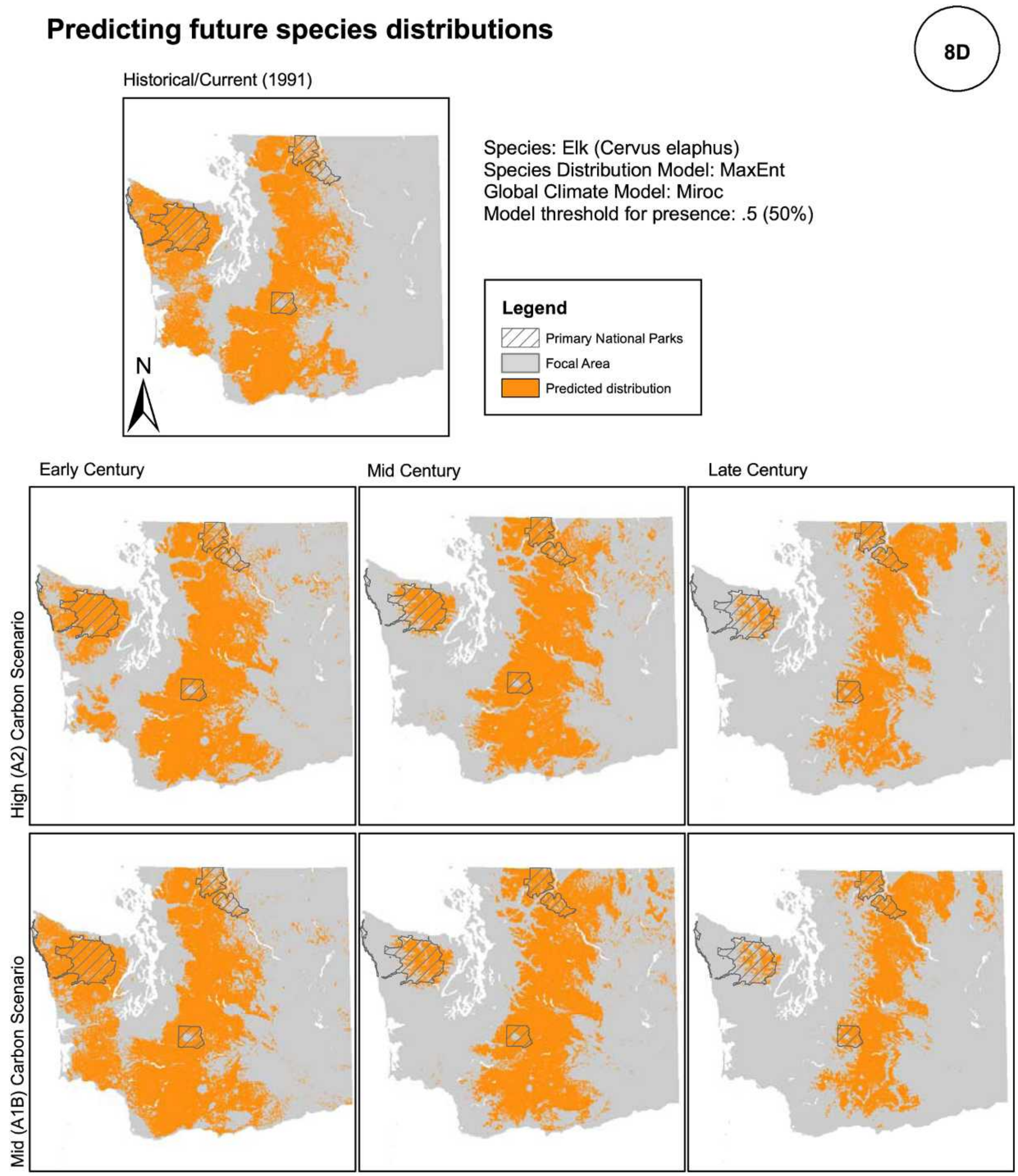

Predicting future species distributions
7D
Historical/Current (1991)
N
Species: Western gray squirrel (Sciurus griseus)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
8A
Historical/Current (1991)
N
Species: Elk (Cervus elaphus)
Species Distribution Model: Logistic Regression
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
8B
Historical/Current (1991)
Species: Elk (Cervus elaphus)
Species Distribution Model: Logistic Regression
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario



Predicting future species distributions
8C
Historical/Current (1991)
Species: Elk (Cervus elaphus)
Species Distribution Model: MaxEnt
Global Climate Model: Hadley
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario


Predicting future species distributions
8D
Historical/Current (1991)
Species: Elk (Cervus elaphus)
Species Distribution Model: MaxEnt
Global Climate Model: Miroc
Model threshold for presence: .5 (50%)
Legend
Primary National Parks
Focal Area
Predicted distribution
N
Early Century
Mid Century
Late Century
High (A2) Carbon Scenario
Mid (A1B) Carbon Scenario