

**POTENTIAL SPECIES DISTRIBUTION OF FIVE NATIVE TREE  
SPECIES FOR HISTORICAL AND PROJECTED FUTURE  
CLIMATES IN NEW BRUNSWICK, CANADA**

by

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## **Abstract**

As part of this report, I develop a series of species distribution models (SDMs) to assess the potential species distributions (PSD) of five native tree species in the province of New Brunswick (NB) for historical (i.e., 1950–2005) and projected, future climate scenario, representative concentration pathway 8.5, for three consecutive periods, 2006–2035, 2036–2065, and 2066–2100. Central to the modeling work is inventory plot data of species presence-absence and four modeled abiotic predictors related to plant growth and distribution. The four predictors include (i) photosynthetically active radiation, (ii) growing degree-days, (iii) relative plant extractable soil water content, and (iv) near-surface wind speed. My PSD-results indicate that high-quality habitat in NB for the five target species will deteriorate with continued climate warming, particularly with respect to balsam fir and red maple. The potential range size of suitable habitat in NB (not necessarily actual distribution) for the five tree species will not change significantly under future conditions.

## **Acknowledgments**

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## 1. Introduction

An intriguing attribute of ecology involves understanding the role of site-biophysical drivers and their spatial expression in differentiating plant and animal distributions in both space and time (Guisan and Thuiller, 2005). Over the past 100 years, the global average temperature has increased by approximately 0.6°C and is projected to continue to rise at a rapid rate (Root et al., 2003). It is well documented that climate change over the past 50 years has produced ample changes in species distribution and diversity, see for e.g., Parmesan and Yohe (2003) and Root et al. (2003).

Canada has  $347 \times 10^6$  hectares (ha) of forests, accounting for about 35% of Canada's total land area. In Canada, the rate of climate change is expected to be 10–100 times faster than the natural adaptation capacity of forests (Canada, 2020). Tree growth is influenced by the natural environment. Forests are susceptible to climate change and increasing temperature due to variations in environmental stress (Dombroskie et al., 2010). Developing further understanding of the relationship between species distribution and the environment is important to forest research and management.

To quantify the relationship of species and environment, species distribution models (SDMs) were introduced to combine observations of species occurrence or abundance with estimates of environmental factors in the prediction of species distribution (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). Developing species distribution models



always begins with observations of species occurrences and environmental predictors with the potential to affect the distribution and habitat suitability (HS-scores; Franklin and Miller, 2009). Some researchers have demonstrated that absence data provides useful information on prevalence (Phillips et al., 2009), but it can be misleading when a species and the environment are not in balance or when the species is prevented from occurring in suitable conditions because of historical, biological barriers (Miller, 2010). Many types of ecological datasets lack reliable absence data (Guo et al., 2005), and it is usually difficult to determine if species are absent from an area (Gu and Swihart, 2004). Usually, the only reliable information on ranges of species is about their recorded presence (Jiménez-Valverde et al., 2008).

There are many explanatory predictors which are thought to influence the presence or absence of tree species in landscapes. Prevailing site-biophysical characteristics are known to affect tree growth, limit the presence or absence of tree species, and control their distribution (Woollons et al., 1997). There are four primary environmental regimes controlling potential distribution, including direct gradients of sunlight (or photosynthetically active radiation), heat accumulation, soil moisture, and mineral content of soils (Franklin, 1995; Guisan and Zimmermann, 2000; Franklin and Miller, 2009). By providing estimates of ecological conditions, these data can greatly enhance the capabilities of SDMs (Elith and Leathwick, 2009). In addition, biological processes, and interactions, such as dispersal, competition, predation, and natural or human-caused

disturbances, can also affect the distribution of species (Franklin and Miller, 2009). None of these factors are addressed in my model of potential tree species distribution.

Species distribution modeling is also known as “bioclimatic-envelope modeling” (Box, 1981), “niche modeling” (Stockwell, 2006), “habitat suitability index mapping” (Clark et al., 1993), “predictive vegetation mapping” (Franklin, 1995), “predictive habitat distribution modeling” (Guisan and Zimmermann, 2000), and “habitat suitability modeling” (Hirzel and Le Lay, 2008; Chang and Bourque, 2020). With advancement of Geographic Information Systems (GIS) and associated statistical techniques, application of SDMs has been rapidly expanding (Guisan and Zimmermann, 2000). The utility of GIS helps SDMs translate the species-environment relationship into geographic space.

To predict the range of species in the future under global warming, species distribution models are now being used to interpolate or extrapolate from point observations over space and time, which yields a predictive map (Franklin and Miller, 2009). Interpolation fills the holes in the geographic and environmental space where the original data is located. Extrapolation is the process of predicting a time or place that is geographically or environmentally distinct from the place of measurement (Bahn and McGill, 2013). However, it is suggested that the ability of SDMs may be limited when predicting climate-driven distribution shifts as strong extrapolation beyond the environmental data exploited for model building can increase the uncertainty in model projections (Charney et al., 2021).

SDMs also have other limitations in their application. For instance, most practitioners use abiotic predictors alone, and very few SDM studies explicitly include predictors describing biological interactions (Guisan and Thuiller, 2005; Baah-Acheamfour et al., 2017). This is because in most datasets, environmental effects are confounded with those of competitors and mutualists (Elith and Leathwick, 2009), and it is often difficult to distinguish the relative importance of fitted abiotic and biotic predictors (Guisan and Thuiller, 2005). Although the consequences may not be too severe in models for understanding interpolation-style predictions, it may have a profound influence on extrapolation, due to, e.g., global warming and introduction of invasive species, because of competitors, mutualists, and conspecific attractions (Elith and Leathwick, 2009).

In this report, I employ a series of SDMs with the R-package, *sdm* (Naimi and Araújo, 2016), to examine the potential species distributions of five tree species in the province of New Brunswick (NB) for historical (i.e., 1950–2005) and projected future climate scenarios of 2006–2035, 2036–2065, and 2066–2100. Habitat suitability scores (or HS-scores, in short; Chang and Bourque, 2020) has an SDM-output range from 0.0 to 1.0. These HS-scores indicate how close the local environment is to the species' optimal growing conditions. The high values for a species stand for the most suitable areas and the potential presence of that species, whereas low values represent poor site quality and the potential absence of the species (Hirzel et al., 2006). The species investigated here include:

- i. three softwood species, i.e., balsam fir [*Abies balsamea* (L.) Mill.], black spruce [*Picea mariana* (Mill.) B.S.P.], red spruce (*Picea rubens* Sarg.); and
- ii. two hardwood species, red maple (*Acer rubrum* L.) and yellow birch (*Betula alleghaniensis* Britton).

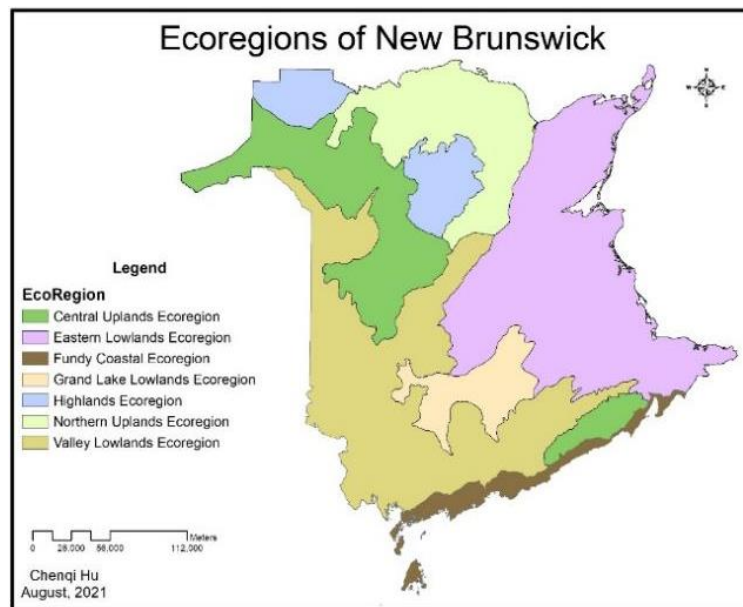
The primary input to the construction of SDM is based on presence-absence data of the five tree species gathered from NB's provincial network of permanent sample plots (i.e., PSP's; Porter et al., 2001) and four digital, abiotic surfaces, i.e., photosynthetically active radiation, growing degree-days, relative plant extractable soil water content, and near-surface wind speed. Soil fertility (SF) is excluded in this study because SF maps with a spatial resolution suitable to support my projections for NB do not exist.

## **2. Methods and Materials**

### **2.1 Study Area**

The study area is the province of New Brunswick (NB), Canada (44°30'–48°4'N, 63°46'–69°2'W), bordering with the USA State of Maine and the Canadian Province of Nova Scotia. NB is divided into seven ecoregions, namely (i) the Highlands, (ii) Northern Uplands, (iii) Central Uplands, (iv) Fundy Coast, (v) Valley Lowlands, (vi) Eastern Lowlands, and (vii) Grand Lake (Fig. 1). They are characterized by their climatic differences and tree species distribution patterns influenced by various climate-related factors (e.g., temperature and precipitation; Zelazny et al., 2007). The climate of NB is

primarily controlled by the migration of airmasses coming from the Polar Regions and extratropical airmasses from the Gulf of Mexico and the Atlantic Ocean (Greenbank, 1956). NB mainly belongs to the temperate broad-leaved and needle-leaved forests (Zelazny et al., 2007). Forests cover about 83% of the NB land base (NB Department of Natural Resources). Public forests of NB are composed of 55% spruce-fir, 32% hardwood species, and 14% other softwood species (Chen et al., 2017).



**Fig. 1.** Seven ecoregions of NB (Ecological Land Classification), GeoNB website, <http://www.snb.ca/geonb1/e/DC/catalogue-E.asp>.

## 2.2 Species Attributes and Habitat

**Balsam fir** is native to most eastern and central Canada and the northeastern USA. It is distributed in northern temperate forests at an altitude of 0–1700 m, with a cold tolerance between -45.6 and -40.0°C (Thompson et al., 1999; Bannister and Neuner, 2001).

Balsam fir grows most favorably in areas where the average annual temperature is 2–4°C

and precipitation is between 760–1100 mm (Bourque, 2015). It is widely distributed throughout NB, especially in the north and northwest of the province, while red spruce dominates in the east and southwest of the province (Zelazny et al., 2007).

**Black spruce** is a typical species widely distributed in Canada, dominating the boreal forest from the north to the tree line (Zelazny et al., 2007). It is found at 0–1500 m in muskegs, bogs, bottomlands, and relatively dry peatlands (Thompson et al., 1999). The climate of black spruce-dominated areas is cold, with humidity ranging from dry to humid and sub-humid (Burns and Honkala, 1990). In NB, black spruce is commonly found in most areas of the Eastern Lowlands Ecoregion and east of the Highland Ecoregion, where the soil is naturally moist, peaty, and acidic (Zelazny et al., 2007).

**Red spruce** is a cool temperate, shade-tolerant conifer native to eastern North America. It is mostly distributed in New England and southeastern Canada (Nowacki, 2015). In NB, red spruce is the predominant conifer species in the climatically warmer, lower elevation areas. It is more tolerant than balsam fir to acidic soil conditions in the Eastern Lowlands Ecoregion (Zelazny et al., 2007).

**Red maple** is one of the most widely distributed trees in eastern North America. It is considered physiologically tolerant to extreme site conditions, but it grows best on moderately well-drained, moist sites (Burns and Honkala, 1990). Its range extends from western Newfoundland and Nova Scotia to southern Ontario, Minnesota, Wisconsin, and

Illinois; south through Missouri, eastern Oklahoma, and southern Texas; and east to south Florida (Little, 1979). Red maple is an important part of cutovers, and shade-intolerant hardwood stands in the three lowland ecoregions of NB (Zelazny et al., 2007). It makes up 8% of historical tree species by volume in NB crownland forests (Management Alternatives for New Brunswick's Public Forest).

**Yellow birch** is native to northeastern North America. The largest concentration of yellow birch occurs in Quebec, Ontario, NB, Maine, Upper Michigan, and New York State. Yellow birch has an intermediate shade tolerance and grows in cool areas with plenty of precipitation. It is found on moist, well-drained soils of uplands and mountain ravines (Burns and Honkala, 1990). Yellow birch is widely distributed throughout NB but is most abundant in the Central Uplands Ecoregion (Zelazny et al., 2007).

### **3. Species Distribution Modeling**

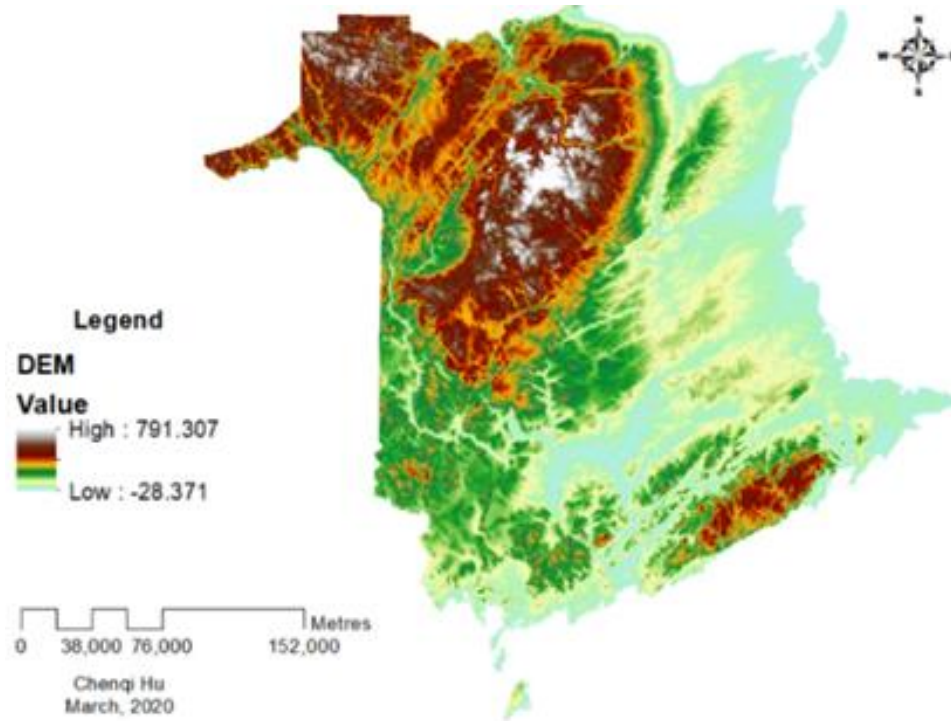
The R package, *sdm*, is an object-oriented reproducible and extensible framework for species distribution modeling that unites different implementations of SDMs in a single package (Naimi and Araújo, 2016). These modeling approaches are state-of-the-art and easy to use. The working procedures of modeling follow the three steps below, namely pre-processing and data requirements, processing and model fitting, and post-processing of the results.

### 3.1 Pre-processing and Data Requirements

This study uses two sources of data, i.e., (i) shapefiles containing geographic-based presence-absence records for the five target tree species; and (ii) raster data, including a digital elevation model (DEM) of NB and four explanatory variables in predicting potential species distribution under future climate change scenarios. The four explanatory, surface variables included those of (i) photosynthetically active radiation (PAR; Bourque and Gullison, 1998), (ii) growing degree-days (GDD; Bourque et al., 2000; Hassan, 2008), (iii) relative plant extractable soil water content (SWC; Bourque et al., 2000), and (iv) near-surface wind speed (WS; Bourque and Bayat, 2015).

The DEM is key to the spatial calculation of species distribution. It affects the calculation of abiotic surfaces of environmental variables, PAR, GDD, SWC, and WS. The DEM is derived from the NASA Shuttle Radar Topography Mission *ver.* 3 data (30-m resolution; Fig. 2) available from the USGS website (i.e., <https://earthexplorer.usgs.gov/>) with the coordinate system in NB Double Stereographic, NAD 1983 CSRS projection.





**Fig. 2.** Digital elevation model (DEM) of New Brunswick.

### 3.1.1 Presence-absence Records

Presence-absence records of the five tree species were obtained from the PSP network established in NB. The Canadian Forest Service and the NB Department of Natural Resources and Energy (NB DNRE; Porter et al., 2001) established the NB PSP program in 1987 to monitor stand structure, develop stand models, as well as to address issues of forest biodiversity and forest management throughout the province.

The PSPs are based on circular plots with an area of 0.04 ha. Trees are sampled within plots, but plot information (e.g., identification of plot, location, size, stand type, stand density, and stand height) has not always been available (Lambert et al., 2005). I chose the initial measurement period for each plot, excluding trees that have died or were of

unknown status.

### 3.1.2 Photosynthetically Active Radiation

Solar radiation drives many biophysical processes through the energy balance and water budget (Bourque et al., 1989). Photosynthetically active radiation (PAR) is the solar radiation within the wavelength range of 400–700 nm (Hall and Rao, 1972). It not only affects tree growth but also influences the geographic distribution of trees (Bourque et al., 2000).

PAR accounts for up to 45% of incident solar radiation. The estimate of PAR is derived from the integration of hourly predictions of incoming solar radiation resolved from DEM-based terrain attributes (slope, aspect, and terrain configuration and sky view factors) and LanDSET (Landscape Distribution of Soil moisture, Energy, and Temperature)-based energy-balance calculations (Bourque et al., 1989; Bourque et al., 2000). A mean mid-afternoon value of 0.70 was used as an estimate of atmospheric transmissivity in solar radiation calculations (Bourque and Gullison, 1998). In my projections of future forests conditions, I assume that the changes in climate will not cause variation in incident PAR.

### 3.1.3 Growing Degree Days

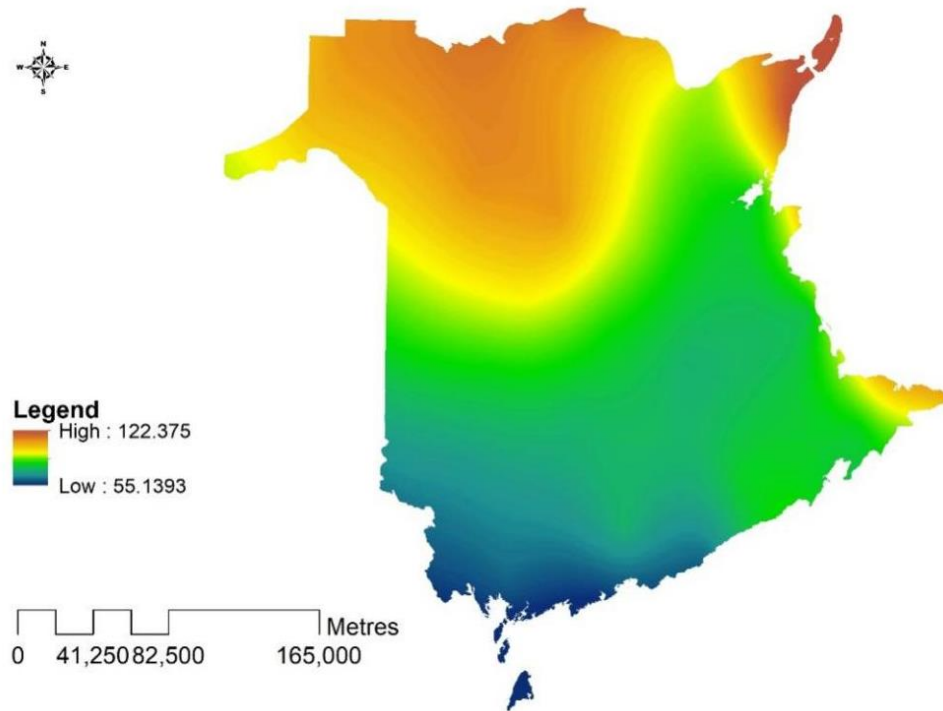
Temperature impacts plant development and growth through regulatory processes, such as evapotranspiration, photosynthesis, plant respiration, in-plant water, and nutrient movement (Hassan et al., 2007a). Plant metabolic processes and growth increase with

temperature (Nilsen and Orcutt, 1996). Growing degree-days is a common measure of heat input (heat accumulation) and, thus, plant growth (Bourque et al., 2000), which is determined by summing the daily difference between the daily mean temperature and a pre-defined temperature threshold (Kimmins, 1997).

Understanding the spatial distribution of GDD is of great importance to sustainable forest management and agriculture (Hassan et al., 2007b). The estimates of GDD were derived from Landsat-7 ETM+ surface reflectance data and Moderate Resolution Imaging Spectroradiometer (MODIS) sensor images (Hassan et al., 2007a), based on the standard definition of GDD, i.e.,

$$\text{GDD} = \sum_{i=1}^{i=n} (\bar{T} - T_{\text{base}}), \text{ when } \bar{T} - T_{\text{base}} > 0, \quad (1)$$

where  $\bar{T}$  is the daily mean air temperature,  $T_{\text{base}}$  is the temperature threshold of 5.6°C (Hassan et al., 2007a), and  $i$  goes from 1 to  $n$ , representing the start and last day of the growing season.



**Fig. 3.** Map of proportional increases in growing degree-days (GDD) for 2066–2100 under RCP 8.5 climate scenario, with historical conditions from 1950–2005 being used as reference.

#### 3.1.4 Relative Plant Extractable Soil Water Content

Soil water plays an important role in plant growth and, thus, species distribution. The requirements and tolerance of soil water vary for different tree species (Oliver and Larsen, 1996). The amount of essential nutrients and available soil water for plant growth can be quantified using indices of soil nutrient and soil water content (Pojar et al., 1987; Farrelly et al., 2011).

The calculation of SWC for NB is based on the soil water content module of the LandSET model, which is influenced by precipitation and lateral flow, percolation, evapotranspiration, surface runoff, and an evaluation of net all-wave radiation ( $\text{MJ m}^{-2}$

day<sup>-1</sup>). Input to the model includes the grid point-by-point DEM-derived topography values, net radiative fluxes, and rainfall amounts (mm day<sup>-1</sup>; Bourque et al., 2000). The non-dimensional value of SWC ranges from 0.0 to 1.0, where 0.0 coincides with the permanent wilting point and 1.0 the field capacity of soils. The SWC-value > 1.0 represents saturation. The exact value of SWC does not affect tree growth-sensitive except near the limits of water deficiency and saturation (Kozlowski, 1968; Li et al., 1989).

### 3.1.5 Near-surface Wind Speed

The wind has both destructive and beneficial influences on trees (Retuerto and Woodward, 1992), such as causing physical damage to plants or promoting physiological processes. Wind speed can affect tree growth by controlling photosynthesis and transpiration (Fogg et al., 1965). Typically, the primary effect of wind on leaf performance is to alter boundary-layer diffusive resistance between the leaf surface and the ambient air, regulating the exchange of CO<sub>2</sub> and water vapor to and from the leaf (Grace, 1974). Some researchers have observed that within a certain wind speed range, the relative growth rate increases with increasing wind speed (Wadsworth, 1959). When the wind speed exceeds an optimal level, the relative growth rate tends to decline for the whole plant and the aboveground components, especially for older leaves (Grace, 1974; Whitehead, 1963).

Near-surface wind speed is estimated based on a three-dimensional wind model. This model is designed to predict wind speed and direction from local measurements of weather

stations and then extrapolate airflow from small-scale estimates of the topography of central NB (Lopes, 2003). Local measurements of initial near-surface atmospheric conditions are obtained from the Saint Leonard Airport weather station (47°09'27"N, 67°50'5"W; Chang and Bourque, 2020).

It is predicted that the maximum wind speed in the NB inland areas will change slightly in the next 90 years (i.e., +0.037% per year). Under climate scenario for representative concentration pathway (RCP) 8.5, wind speed is projected to decrease temporarily in the first 30 years and increase slightly in the remaining time (Bourque et al., 2020), which is not expected to be a significant change. It is assumed that wind speed will be the same for all future simulation periods.

### 3.1.6 Projected Future Climates

Projected climate change for NB were based on Environment Canada's RCM-projections using Environment Canada's fourth-generation regional climate model (i.e., CanRCM4\_CanESM2 at 49×49 km<sup>2</sup> resolution) under RCP 8.5 (Van et al., 2011). RCP 8.5 is also known as the most aggressive, "business-as-usual" climate scenario. It assumes greenhouse gas emissions are increasing over time, which leads to a net radiative forcing of the earth system of 8.5 W m<sup>-2</sup> by 2099 and an increase in the average Earth temperature by 2 to 3.7°C (Stocker et al., 2014).

### 3.2 Processing and Model Fitting

*Random Forest* (a classifier in *sdm*) has been previously used to predict HS under climate scenario RCP 8.5. *Random Forest* arises as a combination of tree predictors (Breiman, 2001). Multiple decision trees and their composites are built together to make the prediction more accurate and stable, where each decision tree is built by a random subset of observations and variables (Evans et al., 2011; Mohapatra et al., 2019). These attributes make *Random Forest* an effective predictive tool. *Random Forest* is relatively immune to overfitting because of the law of large numbers (Breiman, 2001). The algorithm converges to the optimal solution, while avoiding issues known to affect CART (i.e., Classification and Regression Trees) and parametric statistical methods (Evans et al., 2010). Moreover, *Random Forest* can handle the interactions of predictors and demonstrate high performance in non-sampled areas (Yates et al., 2018).

To evaluate the performance of species distribution models, I extracted 75% of the original input data to train the model and remaining 25% to test the model. Further testing of the model was achieved with bootstrapping. Bootstrapping repeats a sampling of the original training dataset with replacement ( $n = 60$  iterations). Each time training data is drawn from a sample from the original data; the observations that are not selected are subsequently used to evaluate the model after each iteration (Naimi and Araújo, 2016).

### 3.3 Post-processing of Results

Model accuracy was evaluated by examining the area under the receiver-operating characteristic curve statistic (AUC) and true skill statistics (TSS). The receiver-operating characteristic curve (ROC) plots the sensitivity (true positives) vs. 1– model specificity (or false positives). The AUC-metric is independent of any threshold and summarizes performance across all possible thresholds (Muñoz and Felicísimo, 2004). AUC ranges from 0.0 to 1.0. A score of 1.0 indicates an ideal performance, and a score of 0.5 is no better than chance (Rubidge, 2011). True skill statistics (TSS) are threshold-dependent performance measurements, i.e.,

$$\text{TSS} = \text{sensitivity} + \text{specificity} - 1. \quad (2)$$

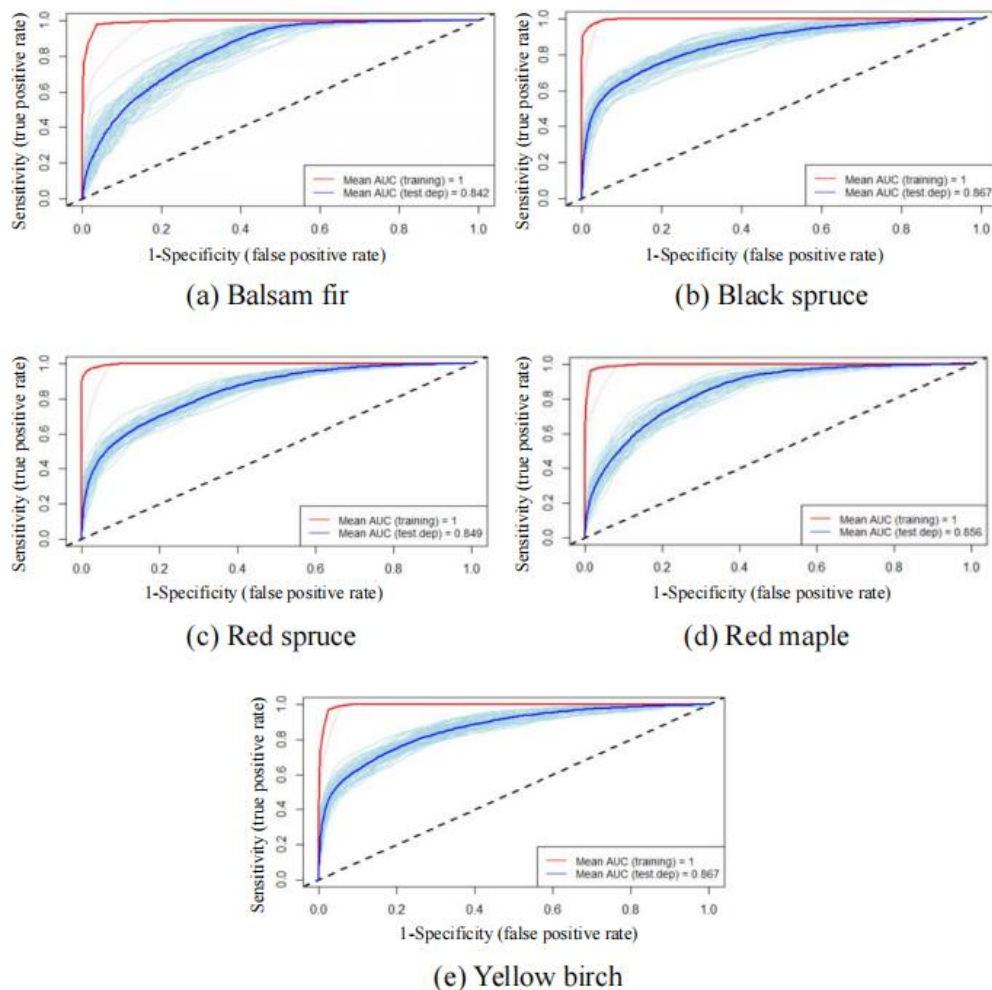
Sensitivity is the possibility of the correct classification of presence in the prediction, and specificity is the probability that the prediction model correctly classifies the absence (Mohapatra et al., 2019). An AUC > 0.8 and TSS > 0.5 indicate strong predictive skill (Swets, 1988; Allouche et al., 2006; Rubidge, 2011).



## 4. Results and Discussion

### 4.1 Prediction Accuracy

The overall accuracy is considered significantly robust for predictions under historical conditions (1950–2005), as all AUCs (based on ROC-curves in Fig. 4) and TSSs are sufficiently  $> 0.8$  and  $0.5$  (Table 1).



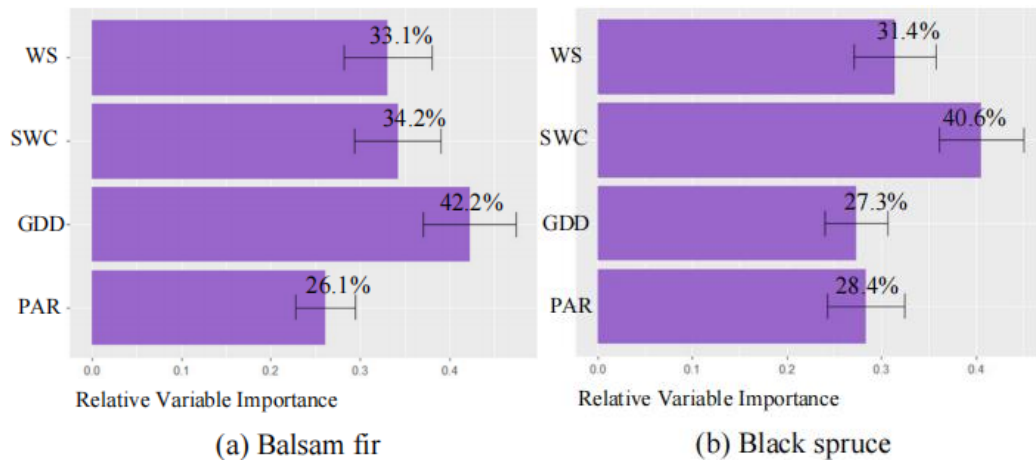
**Fig. 4.** Receiver-operating characteristic curves (ROC) for the five target tree species based on the *Random Forest* classifier (RF). The light blue curves are ROC-curves generated by bootstrapping ( $n = 60$  replicates). Red and dark blue lines represent mean ROC-curves for the training and testing dataset, respectively.

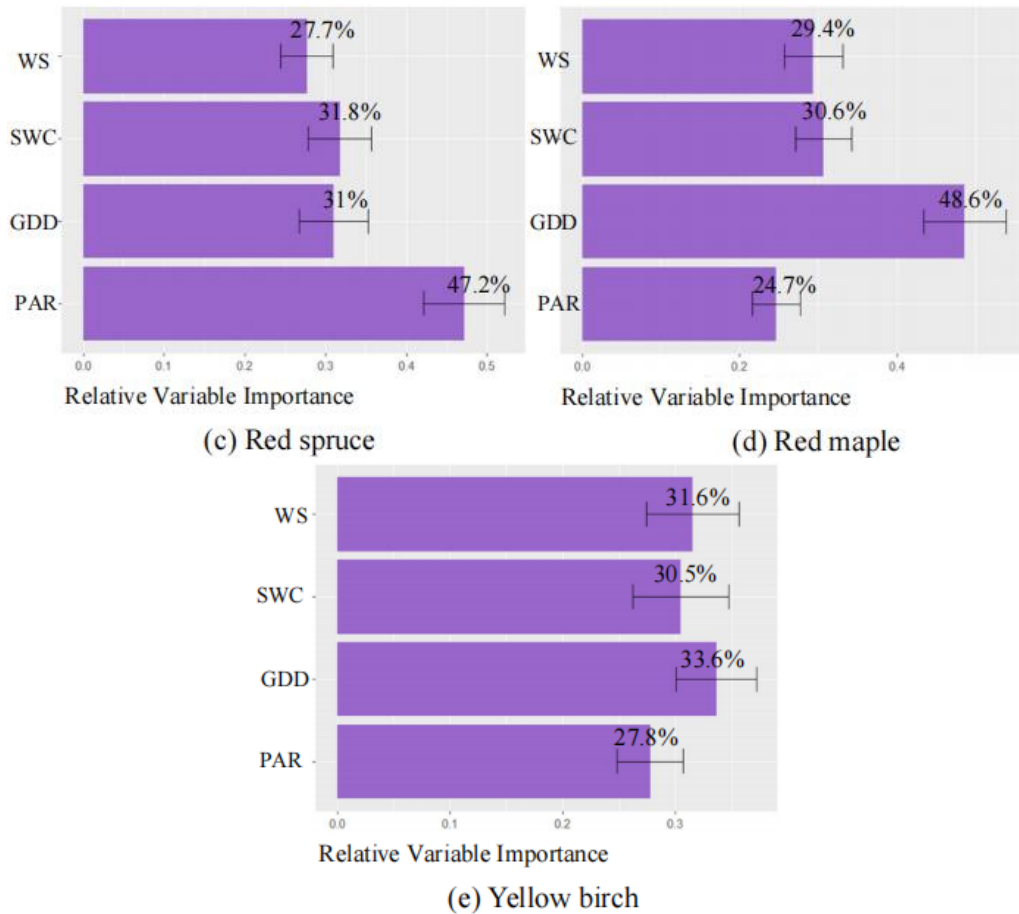
**Table 1.** Model performance statistics based on test data, including the area under the curve (AUC, based on ROCs in Fig. 4), true skill statistic (TSS), and deviance.

Species	AUC	COR	TSS	Deviance
Balsam Fir	0.84	0.61	0.54	0.71
Black Spruce	0.87	0.63	0.58	0.81
Red Spruce	0.85	0.6	0.53	0.98
Red Maple	0.86	0.62	0.56	0.92
Yellow Birch	0.87	0.63	0.58	0.83

#### 4.2 Variable Importance

Variable importance is of practical significance in determining the role of predictor variables in explaining the distribution of species and explaining the output of the model (Naimi and Araújo, 2016). COR (i.e., ‘1 – correlation’) can be considered as a measure of variable importance (Thuiller et al., 2009; see Fig. 5 for testing data). Relative importance increases as COR increases (Naimi and Araújo, 2016).





**Fig. 5.** Relative variable importance for the five target tree species based on mean COR-values generated with the testing dataset.

#### 4.3 Species Distribution for Historical and Future Climatic Conditions

Figures 6–10 provide HS maps of potential tree species distribution (PSD) for the five target tree species from historical conditions (1950–2005) to the end of the 21<sup>st</sup> century (i.e., 2066–2100) under a future climate scenario based on RCP 8.5. A HS-threshold, differentiating good from poor habitat, is often set at 0.5. The tree species is expected to be absent in unsuitable sites, where the HS-scores are below the threshold. Otherwise, if the HS-scores are high enough ( $> 0.5$ ), the species is expected to be present (Hirzel, 2006).

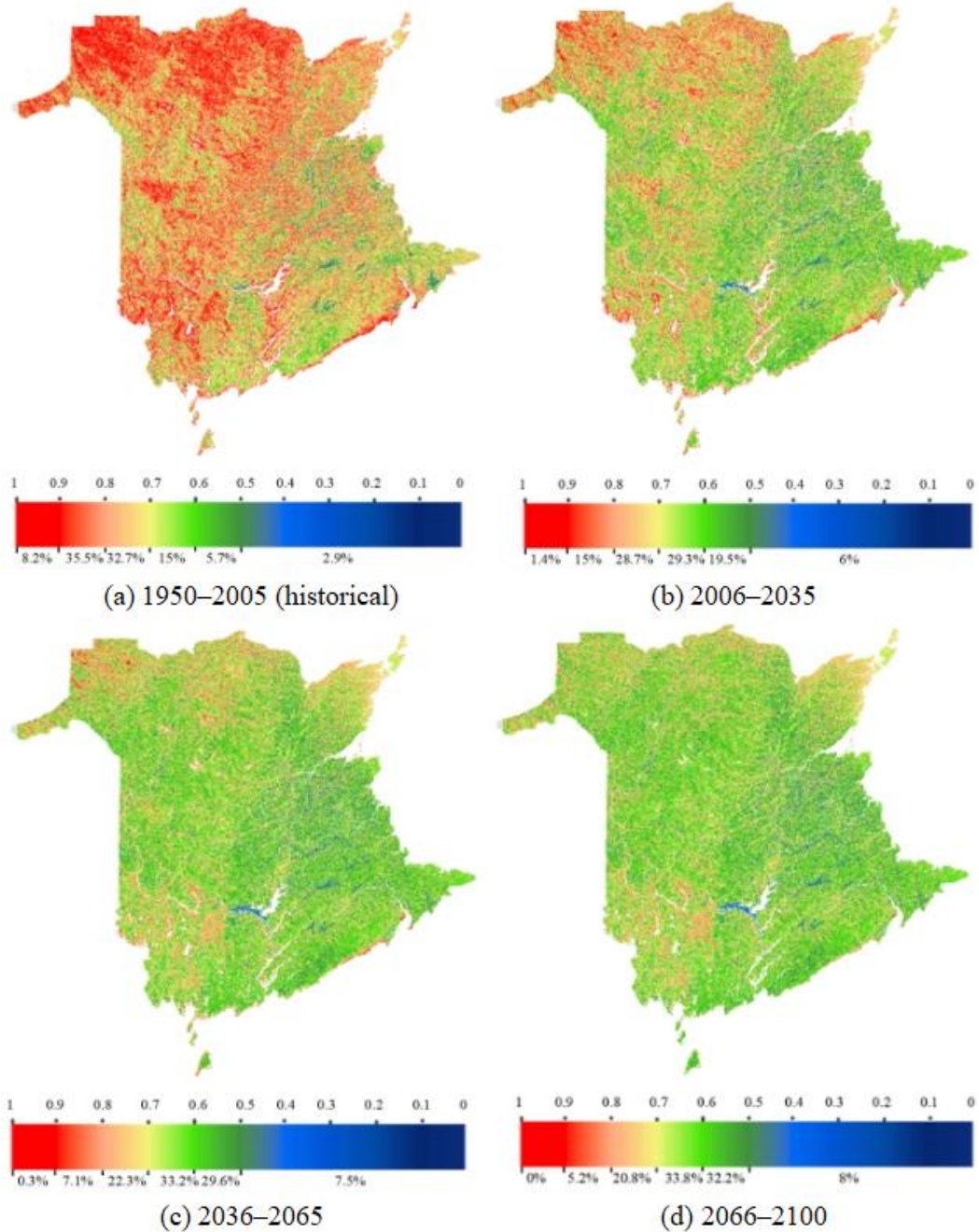
In this research, HS-scores are reclassified into five site classes to help interpret SDM responses, including poor/unsuitable (with HS-scores  $< 0.5$ ), low (0.5–0.6), moderate (0.6–0.7), good (0.7–0.8), and excellent site quality (HS-scores  $> 0.8$ ; Chang and Bourque, 2020). I ignored the areas with no data, as they occupied  $< 0.72\%$  of the total NB landscape. The main features of HS-scores for the five tree species are summarized as follows.

#### 4.3.1 Balsam fir

Balsam fir is widely distributed throughout NB, especially in the north and northwest (Ritchie, 1996; Zelazny et al., 2007). The historical mapping of HS for balsam fir (Fig. 6a) supports this point of view because cumulatively, all good and excellent habitat in NB (represented in yellow to red colors) occupy about 76% of the province. According to the results of relative variable importance, the most important controlling variable of balsam fir geographically is GDD, followed by SWC, WS, and PAR (Fig. 5). The highest HS-scores are distributed within the highlands of the north and south and other cooler regions of the province, next to the inland rivers and large waterbodies (Bourque, 2015; Chang and Bourque, 2020), whereas HS-scores are not particularly ideal in the lowlands of the province due to high GDD and SWC.

Under projected future climate of 2006–2035 (Fig. 6b), regions of low-to-moderate quality sites (overlain by green) expands outward from 20.7–48.8% overall. The most suitable habitat for balsam fir in the central and southern inland regions of the province is

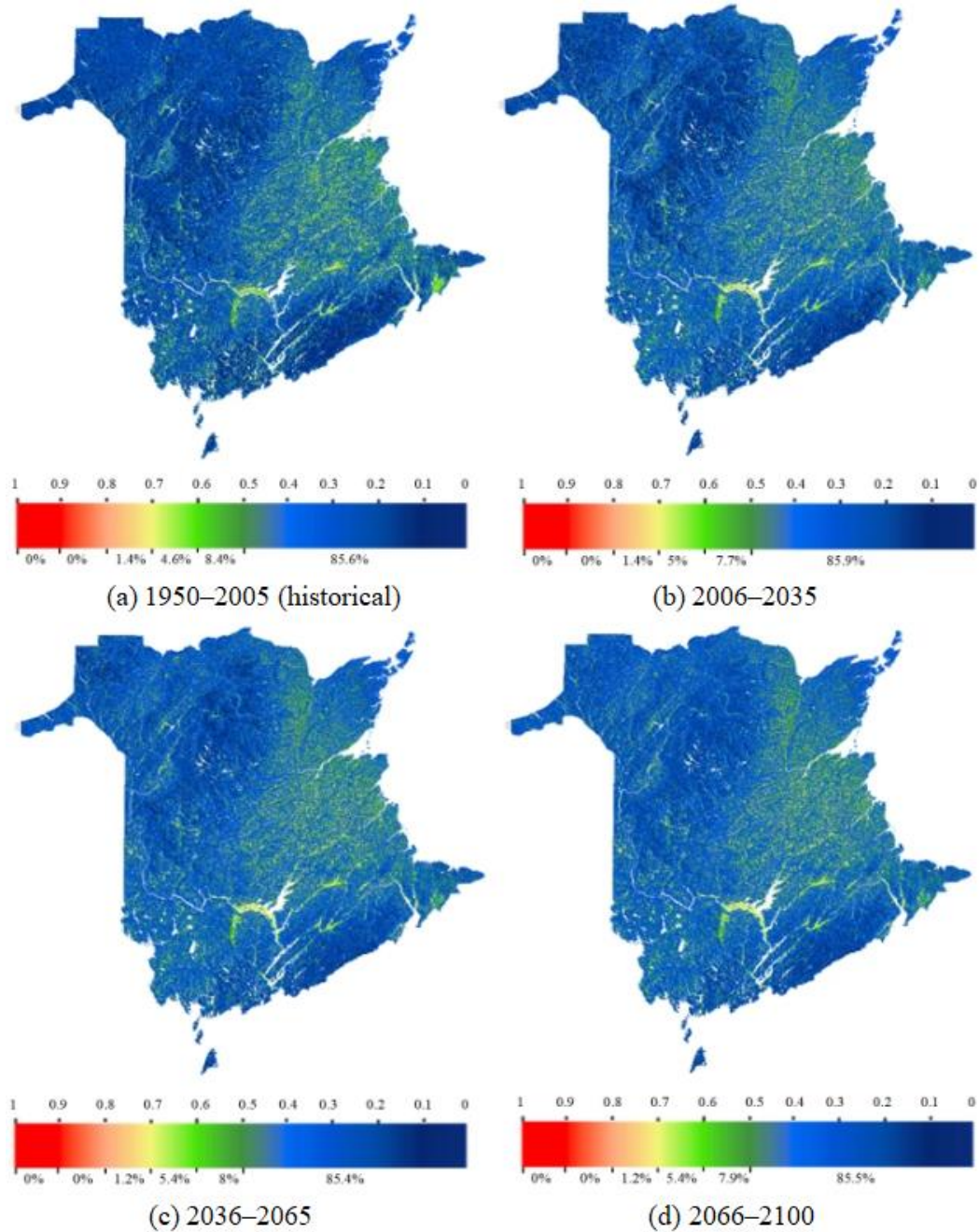
expected to decrease, with high HS-scores ( $> 0.7$ ) being mostly concentrated in the highlands of NB. With continued warming to 2036–2065 (Fig. 6c), low and intermediate habitat will ameliorate, covering about 62.8% of the province. The most suitable habitat (good + excellent site quality) is projected to persist in the high elevation areas of the province and a few riverside areas in the southwest, occupying about 29.7% of the province. By 2100, only 26% of NB is expected to have favorable growing conditions for balsam fir, mainly in the southwest next to major waterbodies that are large and deep enough to offset some of the local warming.



**Fig. 6.** Modeled habitat suitability maps for balsam fir for (a) 1950–2005 (historical) climatic conditions and future conditions for (b) 2006–2035, (c) 2036–2065, and (d) 2066–2100 under an RCP 8.5 climate scenario. The stretched color ramp associated with the modeled HS-scores distribution represents the % of NB occupied by the different site qualities (see legend). Blue to dark green indicates unsuitable habitat and the possible absence of species, while yellow to red indicates sub-optimal and optimal habitat and the potential presence of species; green indicates habitat with low-to-moderate HS-scores and related probable species presence.

#### 4.3.2 Black spruce

In NB, black spruce usually grows in areas where the soil is usually naturally moist and acidic (Zelazny et al., 2007). Under historical conditions, it is not surprising that the greatest determinant of species-habitat variation is SWC (Fig. 5). In the HS map of 1950–2005, most habitat is unsuitable (blue to dark green colors, Fig. 7a). Only 14.4% of the habitat, from low to good, is scattered across the Eastern Lowland Ecoregion and in areas adjacent to major inland rivers and streams. During successive periods (e.g., 2006–2100), the extent of different quality habitat is projected to remain mostly unaffected by continued climate warming associated with a slight increase in SWC, about a 0–16% increase compared to historical conditions (Bourque, 2015).

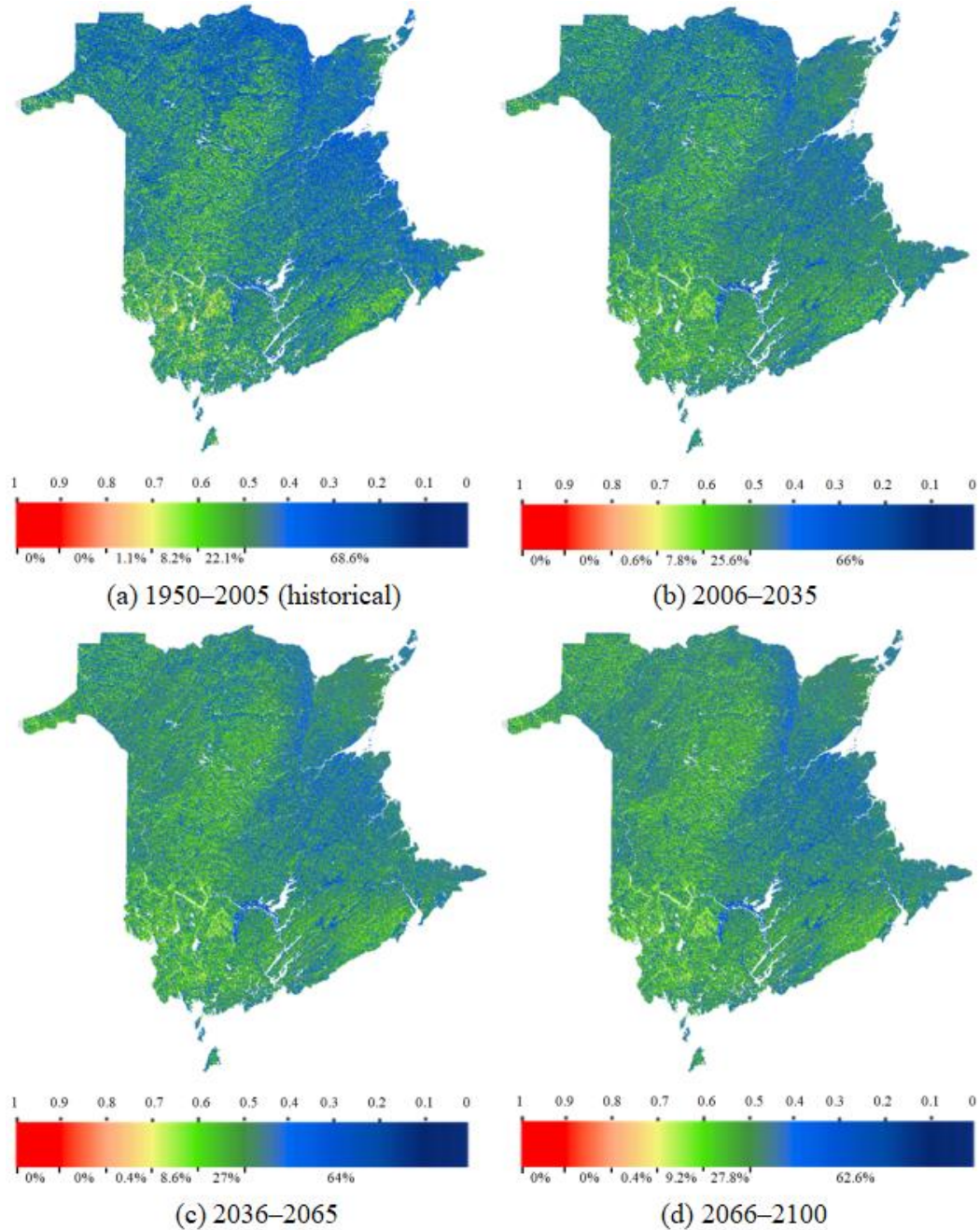


**Fig. 7.** Modeled habitat suitability maps for black spruce for (a) 1950–2005 (historical) climatic conditions and future conditions for (b) 2006–2035, (c) 2036–2065, and (d) 2066–2100 under an RCP 8.5 climate scenario. The stretched color ramp associated with the modeled HS-scores distribution represents the % of NB occupied by the different site qualities (see legend). Blue to dark green indicates unsuitable habitat and the possible absence of species, while yellow to red indicates sub-optimal and optimal habitat and the potential presence of species; green indicates habitat with low-to-moderate HS-scores and related probable species presence.



### 4.3.3 Red spruce

Under historical conditions, PAR has the most significant impact on the probability of red spruce occurrence for its highest COR-value (Fig. 5). High HS-scores  $> 0.6$ , covering about 9% of NB, occur in lower elevation areas with relatively high PAR. From the first to the fourth period (i.e., 1950–2005 and 2066–2100), red spruce habitat with low HS-scores covers more than half of the province (Fig. 8a). At the end of the fourth period, low-to-moderate quality sites (overlain in green) are expected to expand from an initial, historical value of 30.3–37% of NB, especially in the northern and eastern part of NB. Amelioration in low-to-moderate quality sites indicates that red spruce is more likely to occur in the projected future under an RCP 8.5 climate scenario, but the added habitat is not particularly optimal for the species.

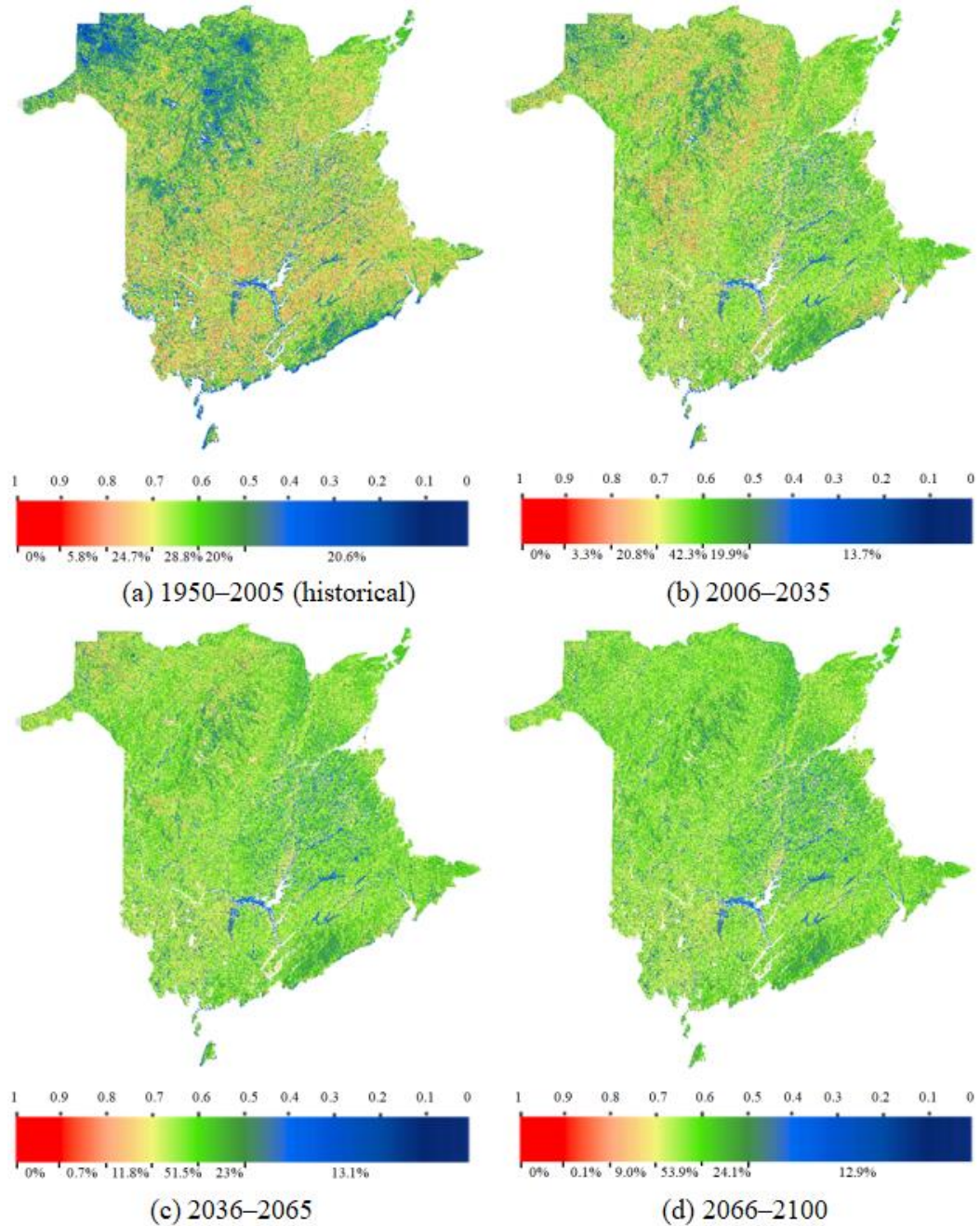


**Fig. 8.** Modeled habitat suitability maps of red spruce for (a) 1950–2005 (historical) climatic conditions and future conditions for (b) 2006–2035, (c) 2036–2065, and (d) 2066–2100 under an RCP 8.5 climate scenario. The stretched color ramp associated with the modeled HS-scores distribution represents the % of NB occupied by the different site qualities (see legend). Blue to dark green indicates unsuitable habitat and the possible absence of species, while yellow to red indicates sub-optimal and optimal habitat and the potential presence of species; green indicates habitat with low-to-moderate HS-scores and related probable species presence.

#### 4.3.4. Red maple

During the first period, most areas in NB are determined to have favorable growing conditions for red maple. GDD shows the most relevance in explaining the spatial variation of red maple for its high COR-value, followed by SWC, WS, and PAR (Fig. 5). High-quality sites  $> 0.7$  occupy 30.5% of the landscape (Fig. 9a), distributed in relatively high GDD, low WS, moderate PAR, and moderately wet areas under historical conditions.

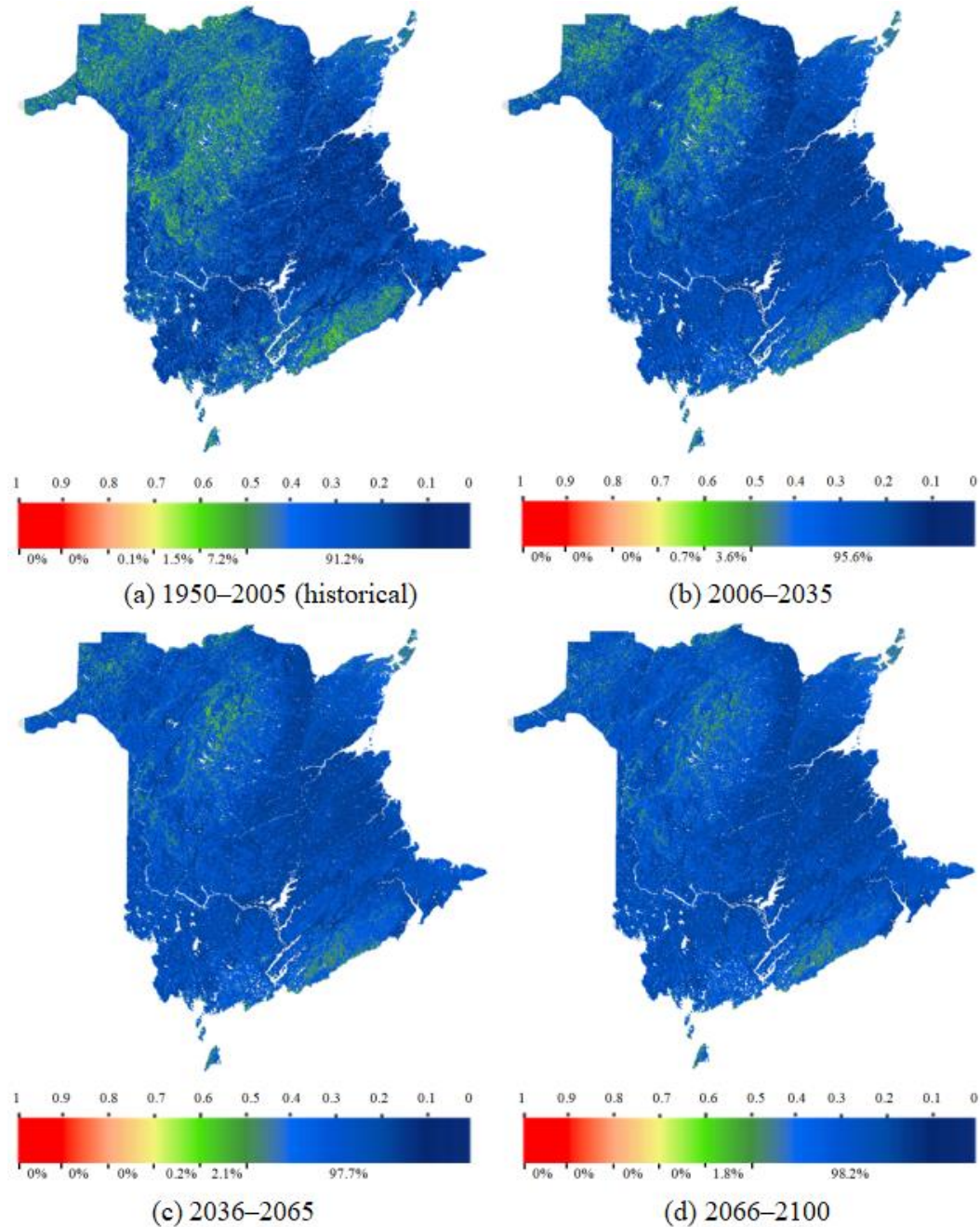
During the following two periods (i.e., 2006–2035 and 2036–2065; Fig. 9), the number of high-quality sites will undergo a gradual decline and shift to high elevation areas, while the habitat with the best potential (with HS-scores  $> 0.8$ ) will largely disappear. As the climate deteriorates further, by the fourth period, only 9% of good-quality habitat is predicted to persist in the province, isolated in lowlands close to major waterbodies. Over 150 years, although the extent of the most suitable habitat is projected to reduce, the overall potential occurrence of red maple will benefit from climate warming, as the extent of low-to-moderate quality sites will significantly increase from an initial, historical value of 48.8 to 78% across the province.



**Fig. 9.** Modeled habitat suitability maps of red maple for (a) 1950–2005 (historical) climatic conditions and future conditions for (b) 2006–2035, (c) 2036–2065, and (d) 2066–2100 under an RCP 8.5 climate scenario. The stretched color ramp associated with the modeled HS-scores distribution represents the % of NB occupied by the different site qualities (see legend). Blue to dark green indicates unsuitable habitat and the possible absence of species, while yellow to red indicates sub-optimal and optimal habitat and the potential presence of species; green indicates habitat with low-to-moderate HS-scores and related probable species presence.

#### 4.3.5 Yellow birch

Under historical conditions, the amount of poor-quality habitat occupies 91.2% of NB. Isolated pockets of low-to-moderate quality habitat (green-colored sites) are distributed in the highlands and along the coast of NB, and correspondingly the low-to-moderate quality sites cover < 8.7% of the province (Fig. 10a). According to the relative importance (Fig. 5), the COR-values of the four environmental predictors are not much different. Perhaps the response of yellow birch to GDD is more prominent with its slightly higher COR-value. Over time, from the 1950–2005 to 2066–2100 periods, the low-to-moderate quality sites will gradually deteriorate from an initial, historical value of 8.7 to 1.8% of NB. During the same time, the extent of unsuitable/poor quality sites is expected to increase to cover about 98.2% of the landscape by the end of the 21<sup>st</sup> century (Fig. 10d), implying that yellow birch is more likely to be extirpated from NB forests under an RCP 8.5 projection.



**Fig. 10.** Modeled habitat suitability maps for yellow birch for (a) 1950–2005 (historical) climatic conditions and future conditions for (b) 2006–2035, (c) 2036–2065, and (d) 2066–2100 under an RCP 8.5 climate scenario. The stretched color ramp associated with the modeled HS-scores distribution represents the % of NB occupied by the different site qualities (see legend). Blue to dark green indicates unsuitable habitat and the possible absence of species, while yellow to red indicates sub-optimal and optimal habitat and the potential presence of species; green indicates habitat with low-to-moderate HS-scores and related probable species presence.

#### 4.4 Discussion

Understanding potential species distribution in landscapes due to global change is essential for the conservation and sustainable management of forests (Elith and Leathwick, 2009). To know where specific tree species may have the potential to grow, SDMs provide an opportunity to predict species response to future conditions.

The simulations indicate that as cold-adapted species, balsam fir and black spruce will not benefit from continued climate warming. High-quality habitat of balsam fir is predicted to deteriorate the most and shift to the cooler regions of the landscape (i.e., adjacent to cold, deep waterbodies and high elevation areas; Bourque et al., 2008). Black spruce will have little to no response to warming, with > 80% of unsuitable habitat in NB. Other modeling efforts reveal that balsam fir and black spruce will undergo a significant decrease (Dombroskie et al., 2010; Mohan et al., 2009; Bourque, 2015) and may move northward under future climate (McKenney et al., 2007).

In my projections, the suitable habitat of red spruce will expand northward in NB with a slight increase of ~6% in its range in the province. The result is consistent with the simulation work by McKenney et al. (2007). While McKenney et al. (2007) argued that if red spruce cannot migrate quickly enough to future conditions, the range is likely to shrink like other northeastern tree species. Sometimes it is challenging to separate red spruce and black spruce from each other in the field, due to their tendency to crossbreed. This may

result in mislabeling and increased error in modeling HS for both black and red spruce (Bourque et al., 2008).

Like balsam fir, climate warming will significantly influence the high-quality sites of red maple at a reduced rate. While the range will expand northward with an 8% increase in size, benefitting it the most compared with the other four species. The germination of red maple seeds will increase with increasing atmospheric CO<sub>2</sub> concentrations (Mohan et al., 2004). Red maple may quickly move with future changes in climate, expanding northward with atmospheric warming. However, it may still undergo a decrease in a highly unfavorable future under a no-dispersal scenario (McKenney et al., 2007; Mohan et al., 2009). With downgrading of favorable habitat, the growth of balsam fir and red maple may show a level of decline during consecutive periods into the future. Adjacent species may be relatively more competitive and may out-compete them in some regions, especially in species with positive tree growth response to climate warming (Dombroskie et al., 2010).

McKenney et al. (2007) predict that yellow birch is likely to migrate quickly in a future climate, like red maple, with its northward expansion. However, yellow birch is not expected to fare as well as red maple, as indicated in this study. Isolated pockets of suitable habitat will undergo gradual decline. By 2100, yellow birch will be restricted to the high-elevation areas and along the coast of NB, which is consistent with the modeling work by

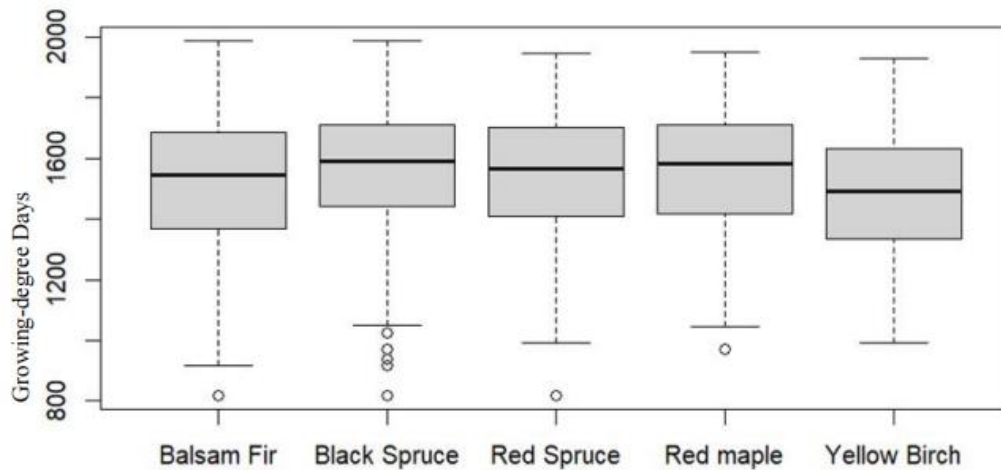


Bourque (2015). A narrow response to increased GDD and, to some extent, moistening of the soils may cause yellow birch trees to decline (Bourque et al., 2008). Besides, extended thaw-refreeze events during winter may have negative implications for yellow birch populations as climate and winter temperatures warm (Bourque et al., 2005; Mohan et al., 2009).

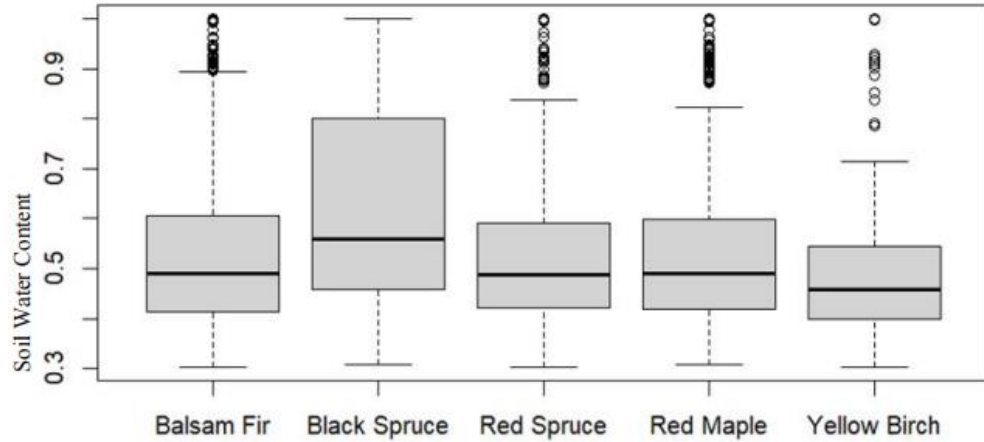
Future climate is likely to differ from historical conditions in NB. Under historical conditions, the records of five species occurrence are observed on sites where the GDD ranges from 800–2000°C (Fig. 11), and the median of SWC is around 0.55 (Fig. 12). Under an RCP 8.5 climate scenario, the estimates indicate that GDD will increase at least in 50% of NB by 2100 (Fig. 3), and SWC is expected to improve slightly with continued warming and increased precipitation (Bourque, 2015).

Extrapolation is required in SDMs to predict the unsampled combinations. In SDM simulations, as the data may not fully represent the species' niche (i.e., collected from all environmental conditions, where the species can occur), may lead to spurious extrapolation to novel conditions and some unrealistic fits (Williams and Jackson, 2007; Zurell et al., 2012). Besides, none of the biotic predictors is considered in my work (e.g., dispersal, competition, predation, and natural or human-caused disturbances; Franklin and Miller, 2009), which may influence my understanding of extrapolation-type predictions (Elith and Leathwick, 2009). Depending on the dynamics of environmental change,

currently unobserved parts of species' niches may become open in the future (Williams and Jackson, 2007). However, overpredictions may also happen in some regions, where robust extrapolation exists (Charney et al., 2021). For instance, in my projections, cold-hardy species like balsam fir may be overpredicted in areas with high GDD with continued climate warming. Species that are more likely to migrate into future climates, such as red maple and yellow birch (McKenney et al., 2007), show no clear signs of success in our projections.



**Fig. 11.** Boxplots of growing-degree days collected from observations from individual PSP where the five species are present.



**Fig. 12.** Boxplots of soil water content collected from observations from individual PSP where the five species are present.

More research is needed on the influence of extrapolation, including interactions in the models (Zurell et al., 2012). Determining the spatial and temporal limits to extrapolation now becomes one of the fundamental gaps to improve the ability of SDMs to replicate tree species distributions (Yates et al., 2018; Charney et al., 2021). Additionally, process-based SDMs might be preferable to occurrence-based, correlative SDMs when predicting species response under new conditions. However, process-based models need vast amounts of experimental data and can only operate at specific spatial scales (Record et al., 2018; Sequeira et al., 2018). Combining occurrence-based, correlative SDMs with process-based SDMs may benefit future research and tree species distribution modeling (Charney et al., 2021).

## 5. Concluding Remarks

My study demonstrates the potential species distribution of five commercial, native tree species in NB by employing a series of SDMs with the *sdm* package (Naimi and Araújo, 2016). I combine observations of species occurrence (i.e., presence-absence records) with four abiotic variables, including PAR, GDD, SWC, and near-surface WS. The presence-absence records from the NB PSP program were constructed from first census measurements taken between 1987–1990.

Projected HS-scores indicate that high-quality habitat across five target tree species will deteriorate across NB with continued climate warming, particularly for balsam fir and red maple, with an anticipated decrease of about 50 and 20%, respectively. The potential range size of suitable habitat (not necessarily actual distribution) for the five species will not change significantly under future conditions (< 10%). Black spruce shows little to no response to the warming, with > 80% unsuitable habitat in NB. Similarly, more than 90% of the habitat is unsuitable for yellow birch under historical conditions, and isolated pockets of low-to-moderate habitat are expected to decline. Ranges of red spruce and red maple will tend to expand northward some, under an RCP 8.5 climate scenario.

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## **CURRICULUM VITAE or CV**

Candidate's full name: Chenqi Hu

Universities attended: Bachelor of Science in Forestry 2016–2019 in Nanjing Forestry University; Bachelor of Science in Forestry 2019-2020 in University of New Brunswick

Publications: None

Conference Presentations: None

I started my master's degree study at UNB in 2020. In two years of study, I achieved a GPA of 4.1. I got an A level in most of my courses, including research methods, forest economics, GIS forestry and management, and environmental impact assessment management. I am familiar with ArcGIS software and used it frequently in my graduation report. I completed my graduation report under the guidance of my supervisor and advisors, which is related to the prediction of species range under climate change.

From 2016 to 2020, I successfully completed my study of the “3+1+1” program between Nanjing Forestry University (NJFU) and the University of New Brunswick (UNB). During my study in NJFU, I attended a provincial innovation practice project for university students and participated in innovative experiments on ginkgo cultivation under the guidance of professors. I obtained good grades in many forestry courses, which have established my fundamental understanding and strong interest in forestry.