Climatic niche models and their consensus projections for future climates for four major forest tree species in the Asia–Pacific region

Tongli Wang [a,*], Guangyu Wang [b], John Innes [b], Craig Nitschke [c], Haijun Kang [b,d]

[a] *Centre for Forest Conservation Genetics, Department of Forest and Conservation Sciences, University of British Columbia, 3041-2424 Main Mall, Vancouver, BC V6T 1Z4, Canada*
[b] *Department of Forest Resources Management, University of British Columbia, 2041-2424 Main Mall, Vancouver, BC V6T 1Z4, Canada*
[c] *School of Ecosystem and Forest Sciences, University of Melbourne, Parkville, VIC 3010, Australia*
[d] *Forestry College, Fujian Agriculture and Forestry University, Fuzhou, Fujian 350002, China*

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ABSTRACT

Modeling and mapping the climatic niches of forest tree species and projecting their potential shift in geographic distribution under future climates are essential steps in assessing the impact of climate change on forests and in developing adaptive forest management strategies. It is particularly important for selecting suitable tree species to match future climates for afforestation and restoration of forest ecosystems. Large scale afforestation and reforestation projects have occurred or planned in Asia–Pacific region; however, the direct impact of climate change has not been widely considered. This has been at least partially due to the lack of availability of robust inventory data on forest vegetation and lack of access to appropriate climate data. In this study, we used our recently developed model, ClimateAP, to generate a large number of climate variables for point locations and used an ensemble modeling approach with Random Forest to overcome some limitations that exist with vegetation data. Uncertainty in future climates was incorporated into the analysis through consensus based projections using 12 climate change scenarios. We modeled the climatic niches for four economically and ecologically important forest tree species in the region and projected their shift in geographical distribution under climate change. Unusual patterns in the shift of geographic distributions of climatic niches were found in two species in Southern China. The implications of the projections in forest management for adaptation to climate change are discussed.

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1. Introduction

Climate is the primary factor regulating geographic distributions of plant species (Woodward and Williams, 1987; Davis and Shaw, 2001; McKenney and Pedlar, 2003). Most forest tree species are adapted to a range of climatic conditions, which is referred to as their climatic niche (Peterson et al., 1999; Pearson and Dawson, 2003). Due to the long lifecycle and slow rate of migration of forest trees, unprecedented rapid climate change will likely result in a mismatch between the climate that trees are historically adapted to and the climate that trees will experience in the future (Aitken et al., 2008). Individuals or populations exposed to climate conditions outside their climatic niches will likely be maladapted, resulting in compromised productivity and increased vulnerability of species to disturbance such as insects and pathogens (Hamann and Wang, 2006; Kurz et al., 2008; Fettig et al., 2013). Therefore,

understanding the climatic niches of forest tree species and projecting their potential shift in spatial distributions for the future are important to assess the vulnerability of tree species and to develop adaptive forest resources management strategies under a rapidly changing climate, including assistant migration (Huntley et al., 2010; Alfaro et al., 2014; Rehfeldt et al., 2014a).

Climatic niches can be defined as constituting the climatic component of Hutchinson's (1957) fundamental niche (Pearson and Dawson, 2003). As they are often built based on the observed distribution of the target species, these models thus reflect a realized climatic niche (i.e., resulting from climatic and biotic constraints, such as interspecific competition) (Pearson and Dawson, 2003; Holt, 2009) as opposed to the fundamental niche (i.e., solely based on the species' environmental requirements) (Hutchinson, 1957). As models of this form involves biological and ecological components, thus they are typically referred to as climatic niche models, bioclimatic envelope models or ecological niche models. We used these terms interchangeably in this study.

* Corresponding author.
  E-mail address: tongli.wang@ubc.ca (T. Wang).

The volume of literature using climatic niche models has been rapidly growing in recent years, while debate about the usefulness of the approach has also followed. A recent review suggests that the criticism has often been misplaced in regard to the objectives of the climatic niche models (Araujo and Peterson, 2012). A climatic niche model defines and predicts the suitable climatic habitat rather than the actual distribution of a species, which involves a series of evolutionary and ecological processes (Aitken et al., 2008). Therefore, a climatic niche model is technically not a species distribution model (SDM) but a habitat suitability model (Keith et al., 2008; Anderson et al., 2009). Confusion between these two kinds of models has led to unrealistic expectations about the outcomes from climatic niche models (Araujo and Peterson, 2012). As a result, many now feel that these so-called SDMs cannot meet users' expectation in adaptation decision making or species conservation strategies (Keenan, 2015).

The distribution and potential shift of climatically suitable habitats are the target of many ecosystem management activities. This information allows users to assess the vulnerability and climate change impact for species or ecosystems for adaptation and conservation (Schueler et al., 2014; Keenan, 2015). Bioclimatic envelope models are reasonably suited for informing species selection and assisted migration in reforestation or afforestation (McLane and Aitken, 2012; Gray and Hamann, 2013; Alfaro et al., 2014). Using the species that best match both current and future climates, regenerating stands will have a better chance of remaining healthy, productive and able to maximize their ecological and/or economic value under a changing climate. This is particularly important given the stated policy aim of planting 20 million hectares of forests in the Asia Pacific over the coming years (Rozelle et al., 2000). Climatic niche models, if properly established and interpreted, can provide valuable, first-order assessments of the potential impacts of climate change and provide a scientific basis for developing adaptive strategies in forest management (Huntley et al., 2010; Fettig et al., 2013; Alfaro et al., 2014; Rehfeldt et al., 2014b).

Bioclimatic envelope models have widely been used in North America (Hamann and Wang, 2006; Rehfeldt et al., 2006; McKenney et al., 2007; Wang et al., 2012a) and Europe (Araujo and New, 2007; Buisson et al., 2010; Lindner et al., 2014). However, related studies in Asia Pacific are lagging behind. This is partially due to the lack of vegetation data and limited access to high quality climate data and to a large number of projections for future climates. In this study, we chose three major forest tree species in China including Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook), Masson Pine (*Pinus massoniana*) and Chinese pine (*Pinus tabuliformis* Carr.). We also chose a major plantation tree species in Australia, blue gum (*Eucalyptus globulus* Labill.). Chinese fir and Masson pine are the two most important subtropical coniferous species in China. Chinese fir occupies about 30% of all plantations in China accounts 25% of China's national commercial timber production, thus it plays a major role in environment, timber supply, and human society (FAO, 2006). Chinese pine is the most widely distributed conifer in North China, with a natural range that stretches from northeastern to northwestern China, between latitudes 31°00′ and 44°00′N and longitudes 101°30′ and 124°25′E (Xu, 1993). Within this range it grows as discrete populations in mountain areas at elevations from 100 to 2700 m (Xu et al., 1993). Blue gum, an evergreen broadleaved tree species, is one of the most widely cultivated trees native to Australia (Booth, 2013). It has four subspecies distributed across southeast Australia. The main objectives of our study is to (1) develop climatic niche models for each of the four major forest tree species in the Asia Pacific considering the limitation of vegetation data; (2) identify climate variables that are important in determining the climatic niche for each species; and (3) project climatic niches for future periods addressing the uncertainty in future climates.

2. Data and methods

2.1. Vegetation data

Presence–absence observations for Chinese fir, Masson pine and Chinese pine were obtained from the digital version of Vegetation Map of China (1:1000,000) provided by "Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China" (link: http://westdc.westgis.ac.cn). A shape file of the distribution for each species was generated from polygons with the species present. The shape file was then rasterized at the spatial resolution of 0.008333 arc min (approximately 1 km). Each data point (i.e., a raster pixel) within a polygon of presence was assigned as presence of the species. Similarly, a data point within a polygon of absence was assigned as absence within the range of the species distribution and expanded by 200 km in each of the four directions if possible following Barbet-Massin et al. (2012). Due to a long history of anthropogenic disturbances to forests in China the current distributions of the species are likely to be underestimated. Thus, some of the absence data points were assumed to be false absences. An adjustment was applied to our modeling process to address this consideration (see below).

For blue gum, 7, 172 presence observations were obtained from the Atlas of Living Australia (Atlas) (http://www.ala.org.au). These observations were aggregated from a wide range of data providers including museums, herbaria, community groups, government departments, individuals and universities. As there were no absences demarcated in the observations, pseudo-absence data points (Elith and Leathwick, 2007; Barbet-Massin et al., 2012) were generated with the following steps: (1) generation of grid locations at the spatial resolution of 0.008333 arc min for areas within the range of the species distribution and extended by 200 km in each of the four directions if possible; (2) randomly sampling 50,000 pseudo-absence data points from the grid locations; and (3) elimination of false-absence data points in the modeling process as described below. After the presence–absence datasets were constructed, the elevation for each data point was extracted, based on its geographic coordinates, from a 90×90 m digital elevation model (DEM) obtained from the Shuttle Radar Topography Mission (SRTM). The latitude, longitude and elevation of the datasets were then used to extract climate data.

2.2. Climate data

The availability of a climate data for the Asia Pacific was achieved through the development of a high-resolution climate model, ClimateAP. This model was used to generate climate data across the region. ClimateAP is a climate data downscaling tool developed for the Asia–Pacific region using the same downscaling algorithms used in ClimateWNA (Wang et al., 2012b) which extracts and downscales PRISM (Daly et al., 2008) and WorldClim (Hijmans et al., 2005) 1961–1990 monthly normal data (2.5×2.5 arcmin) to produce seasonal and annual climate variables for specific locations (scale-free) based on latitude, longitude and elevation. The program uses the scale-free data as a baseline, in combination with monthly anomaly data (relative to the 1961–1990 normals) from IPCC AR5 general circulation models (GCMs) to calculate and downscale (i.e., a delta downscaling approach) monthly, seasonal and annual climate variables for future periods. The output of the program includes both directly calculated and derived climate variables. For this study, we generated 66 annual and seasonal climate variables for the point locations with presence and absence of the species for the reference normal period 1961–1990. Monthly climate variables were not considered due to the large number of annual and seasonal climate variables. For the