Predicting the distributions of suitable habitat for three larch species under climate warming in Northeastern China

Wenfang Leng a,*, Hong S. He a,b, Rencang Bu a, Limin Dai a, Yuanman Hu a, Xugao Wang a

a Institute of Applied Ecology, Chinese Academy of Science, 72 Wenhua Road, Shenyang city, Liaoning Province, 110016, China
b School of Natural Resources, University of Missouri-Columbia, 203 ABNR Building, Columbia, MO 65211, United States

Received 24 August 2007; accepted 24 August 2007

Abstract

The larch (Larix) genus is the most important species group in the forest ecosystems in Northeastern China, occupying about 25% of the forest areas. The high tolerance to coldness and relatively fast growth rate make this genus the main species group for forestation. According to the predictions of the global circulation model CGCM3, temperature could rise by 2–4 °C over the next 100 years. Few studies have been conducted on the response of larch species to climate warming in Northeastern China. Such studies are becoming increasingly needed due to the economic and ecological significance of this genus. This paper studies the potential distribution ranges of three larch species under the current and the warming climate conditions. A new classification and regression tree technique, Random Forest, was used to investigate the potential distributions of three larch species, based on 18 environmental variables which reflect the climate, topography and soil conditions of Northeastern China. The results showed that the biological coldness index (BCI) is the most important factor for Dahurian larch, annual precipitation (AP) is the most important factor for Korean larch and elevation (DEM) is the most important factor for Prince Rupprecht larch.

Under the current climate regime, in general, the prediction accuracy for the training dataset is much higher than that of testing dataset. The prediction accuracy for Dahurian larch is much higher than that of other two larch species. Under three climate warming scenarios, the southeast boundary of suitable habitat of Dahurian Larch was modeled to retreat northwestward by 90 km (CGCM3-B1) via 105 km (CGCM3-A1B) to 140 km (CGCM3-A2) scenario. The potential area would thus decrease from 25.5 million ha currently to 13, 9.5 and 7.2 million ha, correspondingly. The northwest boundary of suitable habitat for Korean larch was modeled move northwestward by 100 km (CGCM3-B1) via 125 km (CGCM3-A1B) to 340 km (CGCM3-A2), while the southern boundary may move northeastward 125 km via 170–200 km, respectively. The modeled potential area thus decreased from 14.6 million ha to 14.5, 12.6 and 9.7 million ha, correspondingly. The suitable habitat of Prince Rupprecht Larch was modeled to disappear under each of the three scenarios.

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Keywords: Dahurian larch; Korean larch; Prince Rupprecht larch; Random Forest; Potential distribution; CGCM3 climate change scenario; Northeastern China

1. Introduction

Global annual temperature has increased by approximately 0.6 °C during the past 100 years, and will continue to increase in the next 100 years. The atmospheric concentration of carbon dioxide in 2005 (379 ppm) exceeds by far the natural range over the last 650,000 years (180–300 ppm) as determined from ice cores (IPCC, 2001, 2007). Climate is the most dominant factor affecting species distribution across broad spatial scales (Woodward, 1987; Pearson and Dawson, 2003). Increasing attention has been paid to predict potential tree species distributions under climate warming (Dyer, 1995; Loehle and LeBlanc, 1996; Higgins and Richardson, 1999; Schwartz et al., 2001; Iverson and Prasad, 1998, 2002; Iverson et al., 2004a,b; Prasad et al., 2006; He et al., 2005).

The response of tree species distributions to climate warming is complex, and varies by region due to factors such as current species composition, site conditions, and local microclimate. Results from paleontology research and observation data in the past revealed the northward or upward moving trend of most tree species (Shugart et al., 1986; Van der Hammen, 1989; Hooghiemstra and Cleef, 1995; Pitelka, 1997; Kullman, 1998; Zhong et al., 2004) in response to climate warming. Overpeck et al. (1991) found that in America, the
ranges of several plant species may shift northward by about 500–1000 km over the next 200–500 years if atmospheric CO₂ concentrations double over pre-industrial levels.

Iverson and Prasad (1998) revealed that several tree species in the eastern United States would shift northward by about 100–250 km by the end of 21st century under Geophysical Fluid Dynamics Laboratory (GFDL) and Goddard Institute of Space Studies (GISS) climate warming scenarios. The optimum latitude of suitable habitat moved north more than 20 km for 38–47 species, including 8–27 species moving more than 200 km (Iverson and Prasad, 2002). However, there is a serious lag between the potential movement of suitable habitat and the potential for the species to migrate into the new habitat (Iverson et al., 2004a). There is a relatively high probability of colonization within a zone of 10–20 km from the current boundary, but a relatively low probability of colonization where the distance from the current boundary exceeds about 20 km (Iverson et al., 2004b).

Climate is warming at an unprecedented rate in Northeastern China, where annual mean temperature rose approximately 1.5 °C over the past 44 years (Sun et al., 2005), thus exceeding the magnitude of change at the global level. Temperate and boreal forests occupy a large part of Northeastern China, with an area of about 47 million ha. It can be inferred that climate change would have a great impact on the forests in this region. In addition, increasing human activities such as forest clearing, human migration, and urbanization in past decades have profoundly altered the forest ecosystems and made them sensitive to changes (Chen and Li, 2003).

Observation data demonstrate that tree species have changed greatly in the past century. For example, Dahurian larch forests in the northern Great Xing’an Mountains declined with the shrinkage of frozen soils (Tan and Li, 1995). In Changbai Natural Reserve, alpine tundra and spruce/fir forests decreased from 1975 to 1997, with a concomitant increase of Korean pine and deciduous broad-leaved mixed forests (Chang et al., 2003).

Many forest stand models or gap models were used to predict forest change under varied GCM scenarios. Results of these studies predicted drastic changes in major forest types in which dominant species became extinct or were replaced within a relatively short time period by species better adapted to the new climate conditions (Yan and Zhao, 1999; Yan and Shugart, 2000; Deng et al., 2000; Hao et al., 2001). For example, spruce (Picea koraiensis Nakai)-larch (Larix olgensis var. changpaiensis) forests were predicted to be completely replaced by deciduous species such as oak (Quercus Mongolica) and elm (Ulmus propinqua Koeld) in about 100 years in the Changbai Mountain (Hao et al., 2001) and Small Xing’an Mountains (Deng et al., 2000).

The larch genus is the most important component in the forest ecosystems in Northeastern China, occupying about 25% of the forested area. The high tolerance to coldness and relatively fast growth rate make this genus the main economic species group. Timber production and forestation in Northeastern China are mainly using this species.

However, the current studies on larch species are mainly concentrated on the physiological characters (Wang et al., 1999; Feng et al., 1999) or population characters (Li, 2006; Xing et al., 2006). Hao et al. (2001) showed that larch (L. olgensis var. changpaiensis) forests could become extinct in the Changbai Mountain region based on a gap model simulation. Deng et al. (2000) reported similar results for the Small Xing’an Mountains region. Few studies have been conducted on the response of larch to climate warming over the entire Northeastern China, which are becoming increasingly needed due to the economic and ecological significance of larch.

In this paper, we choose three larch species, Dahurian Larch (Larix gmelinii), Korean Larch (L. olgensis var. Changpaiensis) and Prince Rupprecht larch (Larix principis rupprechti) to study the effects of climate warming on their potential distributions over Northeastern China. The specific objectives of this study are to reveal the potential distributions of the three larch species under three scenarios of warming climate. By doing so, we will also examine the dominant factors that drive the distributions of the three larch species. The findings will be useful for both ecological conservation and economic assessment of larch species under climate warming.

2. Study area and methods

2.1. Study area

Northeastern China is a large region from 115°05'E 38°40'N in the southwest to 135°02'E 53°30'N in the northeast (Fig. 1). The annual mean temperature varies from 11.26 °C in the southeast to −6.87 °C in the northwest Great Xing’an Mountains, and the annual precipitation ranges from more than 880 mm in the southeast to less than 219 mm in the northwest. The great variations in the distribution of solar energy and available water are the primary causes of current vegetation distribution and are the major driving forces in the responses of vegetation distribution to regional climatic change (Zhou, 1997). The general pattern of vegetation in the region is deciduous broad-leaved forests in the warm and

![Fig. 1. Location of Northeastern China.](image-url)
humid southeast, coniferous forests in the cold northwest, temperate grasslands in the dry west, and coniferous/broad-leaved mixed forest in the humid east, with a vast transition area of central plains where historical vegetation cover has long been converted into agricultural land use.

The three larch species are distributed differently within the region. Dahurian larch is located mainly in the north, with an area of about 11 million ha. Korean larch is located in the southeast, with an area of about 0.7 million ha. Prince Rupprecht larch is located in the southwest, with an area of about 30,000 ha.

2.2. Modeling approach

We developed prediction models for the three larch species over the entire Northeastern China. The models are based on the current distributions of the larch species and their relationships with environmental variables. We derived the current climate based on the recordings of 128 major weather stations for the past three decades and the predicted warming climate scenarios from the Canadian Centre for Climate Modeling and Analysis (CCCMA). We built the models based on the current climate, then exchanged the warming climate scenarios data into the prediction models to predict potential distributions of suitable habitat for the three larch species.

A number of modeling approaches for predicting the potential impacts of climate change on species distribution have been developed (Pearson and Dawson, 2003). These have often focused on the identification of a species’ ‘bioclimate envelope’ (alternatively termed ‘climate space’, Huntley et al., 1995; Carey, 1996; Bakkenes et al., 2002; Berry et al., 2002; Pearson et al., 2002) either through techniques that correlate current species distributions with climate variables or through an understanding of species’ physiological responses to climate change (Franklin, 1995; Mack, 1996; Guisan and Zimmermann, 2000).

Predictions of future range shifts have relied on a variety of modeling approaches with different levels of model accuracy. Researchers have studied the uncertainty in species range predictions caused by different models (Pearson et al., 2006; Lawler et al., 2006). Among many alternative techniques, Random Forest was proved possessing good performance in prediction abilities (Lawler et al., 2006; Prasad et al., 2006). Random Forests was first proposed by Breiman (2001). It is a new entry to the field of data mining and is designed to produce accurate predictions that do not overfit the data (Breiman, 2001, 2002; Prasad et al., 2006). Random Forest is a model-averaging approach based on regression or classification trees. Instead of building one tree model, the Random Forest algorithm builds multiple trees using randomly selected subsets of the observations and random subsets of the predictor variables (Lawler et al., 2006). The strengths of Random Forest are that growing large numbers of trees do not overfit the data, and that random predictor selection keeps bias low. It therefore provides better models for prediction (Prasad et al., 2006).

We used a package in R called “randomForest” (Liaw and Wiener, 2002) for our predictions. R is freeware that was developed by researchers who have contributed novel statistical techniques in the form of packages that can be plugged into R (R Development Core Team, 2004). GIS analysis was performed using ArcInfo 9.1. Kappa statistics were obtained via the Map Comparison Kit (Map Comparison Kit 2003) software.

2.3. Spatial datasets preparation

Three larch species’ current distributions (presence/absence) were derived from the 1:1,000,000 vegetation atlas of China (Editorial Board of Vegetation map of China, Chinese Academy of Sciences, 2001). The atlas had been prepared mainly based on field vegetation survey data over the past 50 years, with references to other information derived from airborne and satellite remote sensing images, geology, soil, and climate. Twelve maps in this atlas, which cover Northeastern China, were digitized into ArcGIS (Version 9.1) (ESRI, 2007) and geometric corrected and mosaiced in ERDAS (Version 8.6) (http://gi.leica-geosystems.com/LGISub1x33x0.aspx) to derive larch distribution maps of the study area. The maps were rasterized to a cell size of 1 km × 1 km.

We choose 18 environmental variables, including climate (Ni, 1997), topography, and soils as the prediction variables in this study (Table 1).

The terrain data were derived from the 1:250,000 contour map and reference point map of Northeastern China (NFGIS, 2007). The Digital Elevation Model (DEM) was created and it provided elevation data for the study area. The climatic variables were calculated based on monthly recordings of 128 major weather stations (1971–2000) across Northeastern China. To interpolate the point data into grid data, multivariate regression equations were developed in SPSS (Version 11.5) based on the relationships of the 11 variables to longitude.

Table 1 Variables used to predict current and future larch distribution

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Variable (unit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAT</td>
<td>Mean annual temperature (°C)</td>
</tr>
<tr>
<td>MAiT</td>
<td>Mean January temperature (°C)</td>
</tr>
<tr>
<td>MMT</td>
<td>Mean July temperature (°C)</td>
</tr>
<tr>
<td>MMST</td>
<td>Mean May–September temperature (°C)</td>
</tr>
<tr>
<td>W1</td>
<td>Warmness index (°C month)</td>
</tr>
<tr>
<td>CI</td>
<td>Coldness index (°C month)</td>
</tr>
<tr>
<td>BWI</td>
<td>Biological warmness index (°C month)</td>
</tr>
<tr>
<td>BCI</td>
<td>Biological coldness index (°C month)</td>
</tr>
<tr>
<td>AP</td>
<td>Annual precipitation (mm)</td>
</tr>
<tr>
<td>MSP</td>
<td>May–September precipitation (mm)</td>
</tr>
<tr>
<td>BK</td>
<td>Biological dry–humidity (mm/C month)</td>
</tr>
<tr>
<td>DEM</td>
<td>Elevation (m)</td>
</tr>
<tr>
<td>SD</td>
<td>Soil depth (cm)</td>
</tr>
<tr>
<td>CC</td>
<td>Clay content (%)</td>
</tr>
<tr>
<td>OM</td>
<td>Organic matter content (%)</td>
</tr>
<tr>
<td>SaC</td>
<td>Sand content (%)</td>
</tr>
<tr>
<td>SiC</td>
<td>Silty content (%)</td>
</tr>
<tr>
<td>TN</td>
<td>Total nitrogen (%)</td>
</tr>
</tbody>
</table>

$T_i$ represents the monthly mean temperature from January to December.

$^a$ W1 = $\sum_{i=1}^{n}(T_i - 5)$, if $T_i \geq 5$ °C.

$^b$ CI = $\sum_{i=1}^{n}(5 - T_i)$, if $T_i < 5$ °C.

$^c$ BWI = $\sum_{i=1}^{n}(T_i - 10)$, if $T_i < 10$ °C.

$^d$ BCI = $\sum_{i=1}^{n}(10 - T_i)$, if $T_i > 10$ °C.

$^e$ BK = $2AP/(BW_{i} + 40)$, if $BW_{i} < 40$. BK = $2AP/(BW_{i} + 120)$, if $BW_{i} > 40$. $BW_{i}$ represents the precipitation of May to September.
The results of the ANOVA revealed that the P-value was lower than 0.001, indicating that the regression model was appropriate. The variable maps were made based on the DEM in the Grid module of Arc/Info (Version 9.1). The six soil variables were derived from the 1:1,000,000 soil map of China, supplied by the Institute of Soil Science, Chinese Academy of Science (Shi et al., 2004).

To be consistent with the vegetation map, all environmental variable maps were resampled to a cell size of 1 km × 1 km.

2.4. Sampling

The entire study area contains about 1.22 million cells. The large data volume went beyond the processing capacity of the current state-of-art computer. Furthermore, to establish a statistically testable Random Forests models, we needed to sample subsets of the whole dataset for tree larch species. The exploratory analysis of Random Forests showed that the area (the number of pixels) of a species had a great impact on the prediction results. Thus, different sample sizes were used for the three species based on their areas.

We sampled 10% from the total number of cells where Dahurian larch occurs, 50% from the total number of cells where Korean larch occurs, all cells where Prince Rupprecht larch occurs, and 5% from the total number of cells where no larch occurs as the training sets to establish the Random Forest models.

2.5. Climate change scenarios

The future climate data from 2070 to 2100 of 70 points which fall in or near the range of Northeastern China were downloaded from the Canadian Centre for Climate Modeling and Analysis (CCCMA) for three climate change scenarios (CGCM3-B1, CGCM3-A1B and CGCM3-A2) (http://www.cccma.bc.ec.gc.ca/eng_index.shtml). The models predict that greenhouse gas concentrations could rise to 550, 720 ppm, and exceeding 720 ppm, respectively, by the year 2100.

2.6. Model evaluation

Out-of-bag (Oob) error, commission, omission, and Kappa statistics (including Kappa, $K_{Loc}$, $K_{Hist}$) were used to compare actual distributions with the predicted potential distributions of the current climate. We computed two sets of Kappa statistics for model evaluation. The first was for the training dataset and the second for the testing dataset.

$K_{Loc}$ is a measure for the similarity of spatial allocation of categories of the two compared maps, and $K_{Hist}$ is a measure for the quantitative similarity of the two compared maps (Hagen, 2002; Prasad et al., 2006).

The value range of Kappa is from −1 to 1. The maximal value, 1, indicates perfect agreement, whereas the minimal value, −1, indicates maximum disagreement. A Kappa value equal to 0 indicates that the observed agreement matches the agreement expected by random arranging of all cells (Monserud and Leemans, 1992; Hagen, 2002).

Comparing the similarity of the observed with the predicted distribution maps of larches, we used these criteria: fail (−1 to 0.2), fair (0.2–0.4), good (0.4–0.6), very good (0.6–0.8), and excellent (0.8–1).

3. Results

3.1. Prediction accuracy of Random Forest

The out-of-bag error rate supplied by the Random Forest model is about 9.2%. In addition, we compared the prediction accuracy between species with Kappa statistics, as well as

\[
\begin{array}{ccc|ccc}
\text{Training dataset} & \text{Testing dataset} \\
\hline
\text{Species} & \text{D. larch} & \text{K. larch} & \text{PR. larch} & \text{D. larch} & \text{K. larch} & \text{PR. larch} \\
\text{Kappa} & 0.85 & 0.64 & 0.64 & 0.52 & 0.08 & 0.05 \\
\text{$K_{Loc}$} & 0.89 & 0.96 & 0.76 & 0.96 & 0.98 & 0.46 \\
\text{$K_{Hist}$} & 0.96 & 0.67 & 0.84 & 0.54 & 0.09 & 0.11 \\
\text{Commission} & 0.07 & 0.50 & 0.45 & 0.59 & 0.95 & 0.97 \\
\text{Omission} & 0.04 & 0.04 & 0.24 & 0.04 & 0.02 & 0.54 \\
\end{array}
\]

D. larch represents Dahurian larch; K. larch represents Korean larch; PR. larch represents Prince Rupprecht larch.
commission and omission errors (Table 2). For the training dataset, Random Forest produced the best match of histograms ($K_{hist}$) for Dahurian larch and the best match of pixel similarity ($K_{loc}$) for Korean larch. When both are considered in the overall Kappa statistic, Dahurian had higher values than the other two larch species. Furthermore, commission and omission errors of Dahurian larch were smaller than those of the other two species.

For the testing dataset, Random Forest produced the best match of pixel similarity ($K_{loc}$) for both Korean larch and Dahurian larch (Table 2). When both are considered in the overall Kappa statistic, Dahurian had higher values than Korean larch. In addition, the commission error of Dahurian larch was smaller than that of Korean larch.

In general, the prediction accuracy for the training dataset was much higher than that of testing dataset, and the prediction accuracy for Dahurian larch was much higher than that of other two larch species (Table 2).

### 3.2. Importance of variables

The variable importance values supplied by Random Forest helps us understand what variables are driving the current

![Fig. 3. Observed and predicted distributions of suitable habitat for Larix gmelinii under the current and warming (2100) climate scenarios. A represents observed distributions (Editorial Board of Vegetation map of China, Chinese Academy of Sciences, 2001), while B represents predicted current distributions using Random Forest under current climate. C–E represent potential distributions of suitable larch habitat under CGCM3-B1, CGCM3-A1B, and CGCM3-A2, respectively.](image-url)
distributions of species. The variable importance for one species may be of no consequence to another species.

For Dahurian larch, the coldness index (CI) is the most important variable, with the biological coldness index (BCI) and mean January temperature (MJAT) also being important. The first three variables are therefore temperature-related, indicating that Dahurian larch is primarily temperature-driven (Fig. 2A).

For Korean larch, annual precipitation (AP) is the most important variable, with May–September precipitation (MSP) and mean January temperature also important. The first two variables are precipitation-related, indicating that Korean larch is primarily precipitation-driven (Fig. 2B).

For Prince Rupprecht larch, elevation (DEM) is the most important variable, with mean January temperature, annual precipitation, and May–September precipitation closely packed in second position. These drivers indicate that Prince Rupprecht larch, within the study area, is driven by a combination of topography and climate variables, and indeed the climate variables could be orographically dominated (Fig. 2C).

Fig. 4. Observed and predicted distributions of suitable habitat for *Larix olgensis* var. *changpaiensis* under the current and warming (2100) climate scenarios. A represents observed distributions (Editorial Board of Vegetation map of China, Chinese Academy of Sciences, 2001), while B represents predicted current distributions using Random Forest under current climate. C–E represent potential distributions of suitable larch habitat under CGCM3-B1, CGCM3-A1B, and CGCM3-A2, respectively.
3.3. Potential distribution of larches under the current and the warming climate scenarios

The maps of the three larch species (Figs. 3A and B, 4A and B, 5A and B) visually reflect the results of the Kappa statistics. The current spatial allocation of Dahurian larch and Korean larch are basically captured by the Random Forests Model. The area for Korean larch was highly overpredicted, which is also the reason for the lower Kappa values of Korean larch. For Prince Rupprecht larch, neither the spatial allocation nor quantity is well predicted.

The model predictions for future climate scenarios showed that the southeast boundary of suitable habitat for Dahurian larch may retreat northwestward about 90 km (Fig. 3C) to 105 km (Fig. 3D) to 140 km (Fig. 3E). The potential area of habitat, within Northeastern China, therefore decreased to 13, 9.5 and 7.2 million ha, correspondingly.

The northwest boundary of Korean larch may move northwestward about 100 km (Fig. 4C) to 125 km (Fig. 4D) to 340 km (Fig. 4E). The south boundary of suitable habitat of Korean larch may also move northeastward but the lack of predictor data south of the Northeastern Chinese border prevents an accurate assessment of this potential trend.

The suitable habitat of Prince Rupprecht larch may disappear under each of the three scenarios (Fig. 5C–E), but scant data (both in species distribution and predictors within the study area) preclude an accurate assessment.
4. Discussion

It is important to emphasize that we are not here attempting to model the species distribution for the year 2100, only its potential suitable habitat. There are many reasons why the species would not likely occupy those suitable sites by that time. It is also important to understand the reason why the Random Forest model performed better for some species than for others because we want to know which models are reliable for the different species (Prasad et al., 2006). Dahurian larch comparatively had the best-fit models (based on Kappa, omission and commission) because (a) it has the largest area compared to the other two larch species, (b) it is distributed in an aggregated fashion compared to the other two larch species, and (c) it has a southern limit well within Northeastern China. Korean larch and Prince Rupprecht larch is distributed in a scattered manner, with a smaller area, and adjacent to southern borders which make it difficult for the Random Forest model to achieve high prediction accuracy. Because of these factors, the results for the Korean larch and Prince Rupprecht larch should be considered preliminary.

There are other uncertainty sources in the model results besides those from the model itself. First, because the datasets (vegetation maps, topographic maps, climate data) were limited by administrative divisions (the national boundary), the Random Forests model for the species in this study were built based on their distributions only in Northeastern China as opposed to their whole natural distribution area. This will underestimate the potential distribution area of larch species, especially on the southern end of the distributions of Korean larch and Price Rupprecht larch.

Secondly, because we are only considering potential suitable habitat and not actual distributions for a certain date, we do not take into account several factors that would be important for estimating actual future distributions. These include the physiological changes associated with changed temperature and precipitations, species longevity, reproduction, dispersal ability, interspecific competition, and fragmentation. Species would be expected to adapt to the new environment to some extent. Species with high longevity can remain in refugia in the current habitats for relatively long times. Limited reproduction and dispersal ability would present problems for species to occupy potential habitat at further distances. Furthermore, competition between species will be important as a warmed climate may negatively affect one species group while favouring other species groups. For example, a warmer and dryer climate could benefit the growth of oaks (Quercus) and lead to their adaptation to the new habitats in a relatively rapid manner (Liu and Fu, 2001). This study also does not take into account landscape fragmentation caused by human activities or natural obstacles. Landscape fragmentation would hinder the migration of species by setting barriers on the migration routes (Knoll, 1984). There are also time lag effects for some species in fragmented habitats (Iverson et al., 2004a,b). Thus, fragmentation makes the regional extinction of species that cannot keep up with the shift of suitable habitat more likely to occur. Interestingly, some researchers have shown that human disturbance can accelerate the migration rate of tree species that are favoured by climate warming. For example, clear cutting the northern larch forests in Heilongjiang Province has been associated with shifting northward of the northern boundary of broad-leaved forests by about 290 km between 1896 and 1986 (Chen, 2000).

Therefore, when comparing the results predicted by a dynamic landscape model which considers all above factors within a specified time frame, the results predicted by the Random Forests models may be more drastic. Thus, the results derived from the Random Forest models are basically the potential suitable habitats rather than the actual distribution area of the tree species. Still these models, when reliable, can provide an indication of suitable habitat within which a whole host of factors, most of which are not reliably predictable out 100 or more years, operate to determine the final distribution in a warmed climate.

Acknowledgments

This work received financial support from the China’s Natural Science Foundation (40331008), the Innovation Program of the Chinese Academy of Science (KSCX2-SW-133), the Project of Key Technology and Demonstration on Forestry Ecological Building (2006BAD03A09), and the National 863 plans projects (2006AA10Z251). We are especially grateful to Drs. Louis Iverson, Robert Keane and Xiuzhen Li for improving our manuscript and to Dr. Hongjuan Liu for supplying the climate data.

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