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A generalized interregional nonlinear mixed-effects crown width model for Prince Rupprecht larch in northern China

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ABSTRACT

Crown width is a tree variable that is commonly used as an important predictor in forest growth and yield models that serve as decision-support tools in forestry. Here, we developed a generalized interregional nonlinear mixed-effects individual tree crown width model using data from 3369 Prince Rupprecht larch (*Larix principis-rupprechtii* Mayr.) trees on 116 sample plots that were distributed across the two most important regions in northern China. Because measurements from the same sample plot were highly correlated with each other, random effects at the levels of both sample plots and stands with different site conditions (blocks) were used to develop a two-level nonlinear mixed-effects crown width model. To describe the interregional variability of crown width between the regions, a dummy variable, which accounts for region-specific differences, was introduced into the model. The results showed that the two-level interregional nonlinear mixed-effects crown width model accurately described the regional variability of crown width for Prince Rupprecht larch in northern China. Modeling the random effects at the block level alone led to significantly high correlations among the residuals. However, these correlations decreased significantly when the random effects were modeled at both the block and sample plot levels. Measuring the crown width of four randomly selected Prince Rupprecht larch trees per sample plot is recommended for localizing the mixed-effects crown width model and precisely predicting the crown widths of the remaining trees on each plot.

1. Introduction

A tree crown is a mass of foliage that is distributed on branches that grow outward from the tree trunk. Crown dimensions are significantly correlated with the foliage surface and crown volume, which in turn are related to the scale of the photosynthetic apparatus. Measurements and analyses of crown dimensions are important for quantifying and qualifying tree vigor, growth stage, stability, and the production efficiency of forest stands. Many studies have modeled crown length (Marshall et al., 2003; Tahvanainen and Forss, 2008; Fu et al., 2017a), the crown ratio (Tahvanainen and Forss, 2008; Leites et al., 2009; Fu et al., 2015), and crown width (CW) (Bragg, 2001; Zarnoch et al., 2004; Sánchez-González et al., 2007; Fu et al., 2013, 2017b; Sharma et al., 2016). Crown width is used as an important predictor to develop individual tree-based mortality models (Monserud and Sterba, 1996), above-ground biomass models (Carvalho and Parresol, 2003; Fu et al., 2016a), and tree volume and taper equations (Jiang and Liu, 2011; Gonzalez-Benecke et al., 2014). Crown width can be also used in ecological modeling to predict light interception in the canopy (Oker-Blom et al., 1989; Pukkala et al., 1991). Despite the numerous uses of CW, measuring the CW of each tree on a sampled area is time-consuming and costly. Thus, it is critical to use many sample trees to develop models that accurately predict CW.

Crown width models can be developed either using CW as a function of diameter alone (Foli et al., 2003; Sönmez, 2009; Pretzsch et al., 2015) or a combination of diameter and other tree and stand variables (Bragg, 2001; Fu et al., 2013; Sharma et al., 2016). The former models may be biased when applied to a large geographic scale because CW-diameter allometry is significantly influenced by site quality, stand density, and any other random variabilities caused by stochastic factors. Thus, the prediction bias of a CW model can be reduced by integrating these variables (Fu et al., 2013; Sharma et al., 2016). Methods of developing CW models have evolved from simple ordinary least squares (OLS) regression to linear mixed-effects modeling, and then to nonlinear

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mixed-effects (NLME) modeling (Sánchez-González et al., 2007; Fu et al., 2013; Hao et al., 2015; Sharma et al., 2016). Among these methods, the mixed-effects modeling approach is the most popular, and it has been increasingly applied to develop CW models. Previous studies have proven that the mixed-effects modeling approach analyzes hierarchically structured data more efficiently than any other approach, and it increases the prediction accuracy of the models (Fu et al., 2013; Hao et al., 2015; Sharma et al., 2016).

Prince Rupprecht larch (*Larix principis-rupprechtii* Mayr.) forests occupy approximately 65% of the forested lands in northern China, and it dominates the forest ecosystems of this area (SFA, 2012). These larch forests are mostly managed for timber production, ecosystem or watershed protection, and as habitats for certain wild animals. "Bright coniferous forests" is a special term that is usually used for larch forests, which have a high albedo, to distinguish them from evergreen forests that are composed of *Picea* and *Abies* species (Shi, 1999; Shi et al., 2000). Larch forests in this region are usually characterized by a large amount of biomass and high primary productivity. These characteristics may be related to the high adaptability of the tree species to extremely low winter temperatures, as well as to the efficient use of water from the melting zone of the permafrost soil during the hot and dry summer seasons (Zhou, 1991; Xu, 1998; Abaimov et al., 2000). This is why Prince Rupprecht larch is widely used for afforestation and timber production in the temperate regions of China (Leng et al., 2008). Many studies have demonstrated that larch forests play critical roles in regional carbon storage and carbon cycling (Fang et al., 1998; Zhou et al., 2002; Wang, 2006; Fu et al., in press). Even though many studies have been conducted on this species across the region, they all have focused mainly on biomass and other tree characteristics (Zeng, 2015; Fu et al., in press), and few CW models have been developed thus far for Prince Rupprecht larch in China (Fu et al., 2016b). Specifically, the application of multilevel NLME to CW modeling for this tree species has been largely overlooked.

Although Prince Rupprecht larch has a special adaptability that enables it to grow in different site conditions, the allometric relationship between its CW and other tree characteristics (e.g., diameter and height) varies from one stand to another, and even within the same stand, they may not be constant over time (Fu et al., 2016b). Furthermore, regional CW variability is substantial, and it needs to be considered while making CW predictions at large spatial scales. Thus, we developed a generalized interregional nonlinear mixed effects CW model by applying a two-level mixed effects modeling approach. For this purpose, we used data from 3369 Prince Rupprecht larch trees on 116 sample plots that are located in the two most important Prince Rupprecht larch distribution regions (western and northern Shanxi) in northern China. The CW modeling used individual tree and stand variables, block- (defined as a stand with a specific site condition) and sample plot-level random effects, and one indicator variable that accounted for the effects of regional differences. We also evaluated the effects of having a sub-sample of complementary trees, for which both dependent and independent variables were measured, on the prediction accuracy of the model, because this enables random parameters to be estimated. The proposed generalized interregional nonlinear mixed effects CW model will be applicable for precise CW predictions of Prince Rupprecht larch trees in northern China.

2. Materials and methods

2.1. Study area and data

We used data from 116 permanent sample plot (PSPs) that were established in natural stands of Prince Rupprecht larch on the state-owned Guandi Mountain forest (67 PSPs) (western Shanxi) and the state-owned Boqiang forest (49 PSPs) (northern Shanxi) in northern China (Fig. 1). Western and northern Shanxi are the most important regions where this species occurs in China. Each PSP is square, with an area of 0.04 ha. These PSPs were established in 2015 and nested within a total of eight different blocks. The 67 PSPs in western Shanxi and the 49 PSPs in northern Shanxi were each allocated in four blocks. The PSPs were selected so that they provided representative information for a variety of stand structures and densities, tree heights and ages, and site productivity. Data collection was conducted by the Research Institute of Forest Resources Information Techniques, Chinese Academy of Forestry.

All standing living trees with diameter at breast height (D) $\geqslant$ 5 cm were measured for total tree height (H), height to live crown base (height above ground to crown base, HCB), and four crown radii. The positions of the four crown radii of each tree were determined by two azimuths (Bragg, 2001), where the first azimuth was defined from south to north, and the second azimuth was perpendicular to the first (Bragg, 2001; Marshall et al., 2003). In each quadrant, the crown radii were measured as the horizontal distances from the center of the tree bole to the greatest extent of the crown from the bole. Branch trips were located by vertical sighting with a clinometer.

Crown width was calculated as the half-sum of the four crown radii. Four dominant or codominant trees (the proportion of the 100 thickest trees ha^{-1}) per PSP were identified and measured (Raulier et al., 2003). The ages of the selected trees were recorded by counting the growth rings on increment cores that were taken from the stem at 0.1 m above the ground (Rozas, 2003). For each PSP, dominant D (DD), dominant H (DH), and dominant age were obtained from the averages of these attributes (Du et al., 2000). The relationships of CW with the three tree variables (D, H, and HCB) and two stand variables (DH and DD) are shown in Fig. 2.

Because model validation is one of the most important procedures that ensures the credibility and confidence of developed models, we validated our CW model by randomly dividing the PSPs into two groups: one for model fitting and the other for model validation. The model fitting dataset consisted of 2250 trees from 69 PSPs, while the model validation dataset consisted of 1119 trees from 37 PSPs. Summary statistics of the measurements of the individual tree characteristics and relevant stand characteristics are presented in Table 1.

2.2. Base model

Taking a nonlinear relationship between CW and D into account (Fig. 2), our modeling began with fitting the basic mathematical functions (hereafter termed the base model) to the data, and this was followed by expanding the best performing base model by integrating various covariate predictors. Fu et al. (2013) developed a logistic CW model (1) using D, H, HCB, and DH as covariate predictors for Chinese fir (*Cunninghamia lanceolata*). They also reported that the CW model developed using this logistic function [model (1)] was less biased than models that incorporated power, asymptotic, or exponential functions. We also found that this model form [model (1)] exhibited the best performance, and, therefore, we used model (1) as a base model to develop an interregional nonlinear mixed-effects CW model.

$$CW_{ijk} = \frac{\phi_1 + \phi_2 DH_{ij}}{1 + (\phi_3 + \phi_4 HCB_{ijk}) \exp\left[-(\phi_5 + \phi_6 H_{ijk}) D_{ijk}\right]} + \varepsilon_{ijk} \quad (1)$$

where CW_{ijk}, HCB_{ijk}, H_{ijk}, and D_{ijk} are the CW (m), HCB (m), H (m), and D (cm), respectively, of the k^{th} tree in the j^{th} sample plot in the i^{th} block; DH_{ij} is the DH (m) of the j^{th} sample plot of the i^{th} block; ε_{ijk} is the error term; and $\phi_1 - \phi_6$ are parameters to be estimated.