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Modelling a system of nonlinear additive crown width models applying seemingly unrelated regression for Prince Rupprecht larch in northern China

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ABSTRACT

Crown width (CW) is an arithmetic mean of two diameters perpendicular to each other and obtained from measurements of four crown radii (crown components) consisting of east, west, south and north crown width. CW is one of the important tree variables in forest growth and yield modelling, and forest management. An accurate approach of obtaining crown measurements can lead to a high accuracy of prediction. Since the additivity properties of CW components and their inherent correlations have not been addressed so far, in this study we introduced a nonlinear seemingly unrelated regression (NSUR) emphasizing the additivity and inherent correlations to develop a system of CW models. We used a large dataset from a total of 3369 Prince Rupprecht larch (*Larix principis-rupprechtii* Mayr.) trees within 116 permanent sample plots allocated in northern China. The results from NSUR were compared with those from two commonly used additive approaches: adjustment in proportion (AP) and ordinary least square with separating regression (OLSSR). In addition, regional effect on CW components was introduced into the CW model system through an indicator-variable modelling approach. The results showed that (1) the effect of region on CW components was highly significant; and (2) NSUR, AP and OLSSR well ensured the additivity property of a system of the CW models. It was also found that overall the prediction accuracy of NSUR was much higher than those of AP and OLSSR. This study focuses more on the development of methodology that can be applied to develop a system of CW models for other tree species.

1. Introduction

Tree growth and yield models are commonly used as decision-support tools in forest management (Canavan and Ramm, 2000; Soares and tomé, 2001). One of the important predictor variables in the models is the measure of tree crown defined by crown length (Marshall et al., 2003; Tahvanainen and Forss, 2008; Fu et al., 2017), crown ratio (Tahvanainen and Forss, 2008; Leites et al., 2009; Fu et al., 2015), or crown width (CW) (Bragg, 2001; Zarnoch et al., 2004; Sánchez-González et al., 2007; Fu et al., 2013; Sharma et al., 2016). CW is often defined as an arithmetic mean of two crown diameters obtained from measurements of four crown radii (crown components), called east crown width (CW_E), west crown width (CW_W), south crown width (CW_S), and north crown width (CW_N), which represent two azimuths (Bragg, 2001). It is a useful measure of tree vigor (Assman, 1970; Hasenauer and Monserud, 1997; Hynynen et al., 2002), mortality (Monserud and Sterba, 1996), and above-ground biomass (Carvalho and Parresol, 2003; Fu et al., 2016). CW can be also used in ecological modelling to predict light interception in canopy (Oker-Blom et al., 1989; Pukkala et al., 1991). However, measuring the CW of every sampled tree is costly and time consuming (Bragg, 2001; Sönmez, 2009; Fu et al., 2013). Thus, developing accurate prediction models of CW using a large number of sample trees becomes very critical.

Crown width estimates are obtained from measurements of stand and tree characteristics, which serve as input information to deterministic or stochastic CW models (Biging and Wensel, 1990; Baldwin and Peterson, 1997; Bragg, 2001; Sönmez, 2009). The development of CW models have evolved from simple ordinary least squares (OLS) regression to nonlinear mixed-effects (NLME) modelling (Sánchez-González et al., 2007; Fu et al., 2013; Sharma et al., 2016). All existing CW models have been developed as a function of tree variables (diameter at breast height, total tree height, height to crown base, and the height-diameter ratio) and stand variables (dominant height, site index, and stand density) using OLS regression

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or an NLME approach. However, none of these methods have accounted for differences among the relationships between each of four crown components and predictor variables of CW models. In addition, correlations among the crown components are often neglected. As a result, these CW models have fallen short of statistical efficiency in parameter estimation. These limitations might result in low prediction accuracy of the CW models (Tang et al., 2015).

When multiple crown components (CW_E, CW_W, CW_S, and CW_N) are considered, it is desirable to have a property of additivity in the estimation of CW (i.e., half of the predictions for the crown component sums to the CW prediction). In forestry, three methods are often used for forcing additivity of a set of the nonlinear models, including adjustment in proportion (AP), OLS with separating regression (OLSSR) and seemingly unrelated regression (SUR) (Parresol, 1999, 2001; Tang et al., 2001, 2015; Tang and Wang, 2002; Fu et al., 2016). AP directly partitions the total CW of a tree into its four crown components (CW_E, CW_W, CW_S, and CW_N) by weighting, whereas a total CW regression function is defined as the half sum of the separately calculated regression functions of the crown components in OLSSR. However, neither the AP nor OLSSR models account for inherent correlations among the crown components. SUR, which is also known as a joint-generalized least square regression, proposed by researchers in the 1980s (Parresol, 1999), is more flexible than AP and OLSSR, but more difficult to employ (Parresol, 1999, 2001). SUR could be used to account for statistical dependencies (e.g., contemporaneous correlations) among sampled data, and the detailed procedures of forcing additivity using SUR can be found in Parresol (1999, 2001).

Recently, SUR has been increasingly used to develop various forest additive models, especially a system of additive biomass equations (Parresol, 1999; Bi et al., 2004; Dong et al., 2015, 2016; Fu et al., 2016). The studies conducted so far have concluded that SUR ensures high efficiency of additivity and strong ability of accounting for correlations among the components. SUR increases the prediction accuracy of the models compared to other non-additive methods such as OLS methods (Lindstrom and Bates, 1990; Vonesh and Chinchilli, 1997). To our knowledge, however, no study has been conducted using SUR to handle the additivity of crown components while CW is modeled.

This study thus aims to develop a system of nonlinear CW models using SUR with data of individual trees from permanent sample plots located in the Prince Rupprecht larch (*Larix principis- rupprechtii* Mayr.) stands in northern China. This study also compares the estimates of CW and crown components obtained from SUR and those obtained from a traditional non-additive (OLS) method and two other additive (AP and OLSSR) methods using a separate validation dataset.

2. Materials and methods

2.1. Data

We used data from 116 permanent sample plots (PSPs) that were established in natural stands of Prince Rupprecht larch in the state-owned Guandi mountain forest (67 PSPs) and the state-owned Boqiang forest (49 PSPs) in northern China (Fig. 1). Each PSP is square shaped with a size of 0.04 ha. The PSPs were laid out in such a way that they could cover a large area with variability of stand structure, stand density, tree size, stand age, and site productivity.

All standing and living trees with diameter at breast height (D) $\geqslant$ 5 cm were measured for D, total height (H), height to live crown base (height above ground to live crown base, HCB) and four crown radii (CW_E, CW_W, CW_S, and CW_N). The positions of four crown radii for each sampled tree were determined by two azimuths (Bragg, 2001). The first azimuth was defined as the direction from south to north, and the second azimuth was perpendicular to the first (Bragg, 2001; Marshall et al., 2003). In each quadrant, crown radii were measured as horizontal distances from the center of tree trunk to the greatest extent of the crown from a trunk. CW was computed by $(CW_S + CW_N + CW_E + CW_W)/2$. Four dominant or codominant trees (the proportion of 100 largest trees per ha) (Raulier et al., 2003) were identified and measured on each PSP. The ages of the selected dominant or codominant trees were recorded by counting growth rings based on increment cores taken from stems at height of 0.1 m above ground (Rozas, 2003). For each PSP, dominant tree D (DD), dominant tree H (DH), and stand age were obtained from the arithmetic means of these attributes (Du et al., 2000).

PSPs were randomly divided into two groups: one for model fitting and the other for model validation. Model fitting dataset consisted of 2250 trees from 69 PSPs while model validation dataset consisted of 1119 trees from 37 plots. The relationships of CW, CW_E, CW_W, CW_S, and CW_N with four predictor variables (D, H, HCB, and DH) are shown in Fig. 2. Summary statistics of measurements for the characteristics of individual trees, and relevant stand characteristics are presented in Table 1.

2.2. Base model

Fu et al. (2013) developed a logistic Model (1) using D, H, HCB, and DH as predictors for CW prediction of Chinese fir (*Cunninghamia lanceolata*). They reported that their CW model provided higher prediction accuracy than other CW models tested (power, asymptotic, linear, and exponential). Therefore, Model (1) was selected as a base function to develop a system of nonlinear CW models in this study.

$$CW = f(\mathbf{x}, \boldsymbol{\beta}) = (\beta_1 + \beta_2 DH)/[1 + (\beta_3 + \beta_4 HCB) \exp(-(\beta_5 + \beta_6 H)D)] + \varepsilon \tag{1}$$

where $\mathbf{x}$ is a covariate vector, which includes D, H, HCB, and DH, $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$ is a 6-dimensional parameter vector, and ε is an error term.

We introduced a dummy variable P to account for CW difference of the Guandi mountain forest farm from Boqiang forest farm (i.e., $P = 0$ for Guandi mountain forest farm and $P = 1$ for Boqiang forest farm). After imposing P on β_1 and β_2, Model (1) takes following form:

$$CW = f(\mathbf{x}, P, \boldsymbol{\beta}) = [\beta_1 + k_1 P + (\beta_2 + k_2 P)DH]/[1 + (\beta_3 + \beta_4 HCB) \exp(-(\beta_5 + \beta_6 H)D)] + \varepsilon \tag{2}$$

where k_1 and k_2 are model parameters and other variables have been defined in Model (1).

$$\begin{cases} CW_E = f_E(\mathbf{x}, \boldsymbol{\beta}) + \varepsilon_E = (\beta_{1E} + \beta_{2E} DH)/[1 + \beta_{3E} HCB \exp(-(\beta_{4E} + \beta_{5E} H)D)] + \varepsilon_E \\ CW_W = f_W(\mathbf{x}, \boldsymbol{\beta}) + \varepsilon_W = (\beta_{1W} + \beta_{2W} DH)/[1 + \beta_{3W} HCB \exp(-(\beta_{4W} + \beta_{5W} H)D)] + \varepsilon_W \\ CW_S = f_S(\mathbf{x}, \boldsymbol{\beta}) + \varepsilon_S = (\beta_{1S} + \beta_{2S} DH)/[1 + \beta_{3S} HCB \exp(-(\beta_{4S} + \beta_{5S} H)D)] + \varepsilon_S \\ CW_N = f_N(\mathbf{x}, \boldsymbol{\beta}) + \varepsilon_N = (\beta_{1N} + \beta_{2N} DH)/[1 + \beta_{3N} HCB \exp(-(\beta_{4N} + \beta_{5N} H)D)] + \varepsilon_N \\ CW = (CW_E + CW_W + CW_S + CW_N)/2 + \varepsilon_T \end{cases} \tag{3}$$