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Individual tree basal area growth models for Chir pine (*Pinus roxberghii* Sarg.) in western Nepal

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ABSTRACT: The individual tree growth models are important decision-making tools in forestry. Age dependent and age independent individual tree basal area growth models were developed for Chir pine (*Pinus roxberghii* Sarg.) in one of the western districts, Rukum district, in Nepal. Data from thirty-five destructively sampled trees, which were representative of all possible stand densities, site productivities, age classes, and size classes of Chir pine forests in the district, were used. Sample trees were felled and diameters and ages were measured on the cut surface of the stump (at 30 cm above the ground). Since measurements from the same stump of a tree were strongly correlated, the autoregressive error structure modelling approach was applied while specifying the model in order to reduce bias. All parameter estimates of the models were significant ($P < 0.01$) and the models described most of the variations of basal area growth ($R^2_{adj} > 0.86$). Residual graphs showed no serious systematic bias for all observed age classes and diameter classes. The age independent growth model showed relatively better fit statistics ($R^2_{adj} = 0.8751$, $RMSE = 4.8494$) than its age dependent counterpart ($R^2_{adj} = 0.8668$, $RMSE = 5.0158$). Because of being more precise and simpler, the age independent model is recommended to apply to both even-aged and uneven-aged stands of Chir pine in the district.

Keywords: autoregressive error structure; age dependent model; age independent model

Effective and efficient forest management is possible only when reliable information about the present and future forest condition is available. Forest growth models serve as important tools in providing reliable information for decision making. Modelling growth and yield has been an intrinsic part of forestry research for several years, and still remains an area of important and active research (Vanclay 1994; Porte, Bartelink 2002). Forest growth models are useful tools for inventory updating, evaluation of silvicultural treatments, harvest scheduling, and management planning (Garcia 1994; Amaro et al. 2003). Based on management objectives, access to the computational facilities and input data, forest growth models may be operational either at stand level or at individual tree level (Vanclay 1994; Porte, Bartelink 2002). Stand growth can be modelled as a function of stand variables such as site index, stand age, stand diameter (e.g. quadratic mean diameter), stand basal area, stand density index, and number of stems (Pienaar, Rheney 1995; Huuskonen, Miina 2007; Gizachew, Brunner 2011). Thus, stand growth models do not describe the growth dynamics of individual trees, and therefore they are usually applicable only to even-aged and homogeneous stands.

The individual tree based growth models describe the growth dynamics of individual trees in a stand. The growth of an individual tree within a stand largely varies due to competition from other trees. Competitive stress to any tree within a stand varies with species, number, size, location of its competitors. The individual tree based growth models are usually developed to describe growth dynamics for structurally complex and heterogeneous stands (Wykoff 1990; Pretzsch 2002; Uzoh, Oliver 2006; Bollandsås, Næsset 2009). In these models, the potential growth of individual trees is reduced by competition index (a measure of competition), which may be either distance dependent (Bella 1971; Biging, Dobbertin 1992; Ledermann, Stage 2001; Rivas et al. 2005) or distance independent (Wykoff 1990; Uzoh, Oliver 2006; Bollandsås, Næsset 2009). Long-time growth series (longitudinal or radial growth) data of individual trees are needed to develop individual tree growth models. Long-term growth series data are obtained either from long-term research plots or national forest inventory plots or stem analysis. In addition, stump analysis data, which has been used to model the individual tree basal area growth in this study, also provides radial growth time series.

The individual tree radial growth models (diameter growth or basal area growth models) are useful to estimate volume growth if information on height growth is available. The individual tree radial growth models are commonly used as sub-models in a growth simulator (Sterba, Monserud 1997; Pretzsch 2002; Hasenauer et al. 2006; Lacerte et al. 2006; Gobakken et al. 2008). The individual tree radial growth models offer a good possibility of exploring detailed management alternatives, because these models can adequately describe the forest growth dynamics (Martin, Ek 1984; Uzoh, Oliver 2008; Subedi, Sharma 2011; Wagle, Sharma 2012). Since basal area growth is highly correlated with volume growth, basal area growth models are preferred to diameter growth models (Wykoff 1990; Monserud, Sterba 1996; Schröder et al. 2002; Andreassen, Tomter 2003; Anta et al. 2006). Many silvicultural and management considerations, for example, thinning intensities, are based on the measurements of basal area growth. In addition, the curves of mean basal area growth are useful tools for effective management of stands as they help estimate the timing of intermediate and final cuts (Hong-gang et al. 2007). The individual tree basal area growth models can be used to update inventories, predict future yield, and to explore management alternatives. Compared to stand characteristics such as mean diameter, mean height, and mean crown diameter, basal area possesses a high degree of exactness on measurement or prediction. Thus, the basal area concept is important and applicable to a wide range of conditions (Hong-gang et al. 2007).

Distance dependent or distance independent individual tree growth models can be developed using either of the two methods: indirect control over the growth with potential modification (Biging, Dobbertin 1992; Pretzsch 2002; Pommerening et al. 2011; Sharma 2013) or direct estimation of growth by regression techniques (Wykoff 1990; Huang, Titus 1995; Rivas et al. 2005; Uzoh, Oliver 2008; Subedi, Sharma 2011). With the indirect method, potential growth is expressed as a function of current size or age of the trees and site index, while competition index and measures of tree vigour are used as modifiers that reduce potential growth (Biging, Dobbertin 1992; Pretzsch 2002; Reed et al. 2003; Pretzsch 2009). However, with the direct method, periodic tree growth is modelled as a function of tree size, site index, competition index, and mean stand characteristics by applying regression techniques (Wykoff 1990; Huang, Titus 1995; Mailly et al. 2003; Rivas et al. 2005; Uzoh, Oliver 2008). In this study, the direct method was applied by using tree size or tree age as independent variable, because potential growth data (i.e. potential diameter growth data of the dominant trees on Chir pine stands) were not available.

Chir pine grows mainly between 900 m and 1,950 m above mean sea level in Nepal. It is by far the most widely planted species in Nepal, i.e. approximately 57% of all trees planted by the Community Forestry Development Project were Chir pines (Jackson 1994). In western Nepal, it takes up a large area of pure Chir pine forests on north- and south-facing slopes, and in some places it is also associated with *Shorea robusta*. It can easily survive and grow faster on poorer sites, which are mostly available for plantation in the hills. It is a pioneer species, once it is established, other fuel and fodder species can regenerate naturally under Chir pine trees. Its growth is faster than that of blue pine (*Pinus wallichiana*) trees. The silvicultural characteristics and uses of Chir pine are available in the literature (e.g. Jackson 1994). Chir pine wood is suitable for construction purposes. Chir pine trees are also tapped commercially for resin, and on distillation, resin yields an essential oil, commonly known as turpentine, and non-volatile rosin. These products are economically very important. The economic contribution of Chir pine forest in Nepal is substantial both on the local and national levels. Therefore, scientific management of Chir pine forest in Nepal is important, but growth models for this species are still lacking. This study thus aims at developing individual tree basal area growth models which will be used for the prediction of basal area growth at an individual tree level. The models presented herein will be useful for effective management of Chir pine forests in western Nepal.

MATERIALS AND METHODS

Study area. Chir pine growth data were obtained from Solabang community forest (CF), which is located in the Musikot Village Development Committee (VDC) of Rukum district (Fig. 1). The district is located in the Rapti zone of the mid-western administrative region of Nepal, and also it is located at 28°29' to 29°0'N latitudes and 82°12' to 82°53'E longitudes with an area of 2,877 km^2. The altitude of Rukum district ranges from 745 m to 5,841 m above mean sea level. The climate (temperature and precipitation) varies from tropical to temperate with a minimum temperature of 0.4°C, maximum temperature 24°C, mean annual rainfall 1,600–2,400 mm. About 29% of the geographical area of the district lies under a steep slope, about 4% of the area is covered by an ancient lake and terraces, about 17% of the area is covered by past glaciated mountain terrains, and 43% of soil falls under the Lithic subgroup. Solabang CF is a natural forest of *Pinus roxburghii* and *Shorea robusta* as the main tree species and has been managed by community forest user groups for the last ten years. The Chir pine forest of Solabang CF is therefore an uneven-aged and mixed-species forest and consists of varying sizes of Chir pine and pole-sized individuals of *Shorea robusta.* Chir pine trees have been tapped by community forest user groups for commercial purposes.

Data. Thirty-five trees representing the majority of diameter and age classes, site productivities, and stand densities of Chir pine stands were identified and felled. Sample trees were felled at a height below 1.3 m (breast height) and the stump cut surface at 0.3 m was prepared with a crosscut saws for larger stumps, a bow saw for medium sized stumps and a hand saw for smaller stumps, and smoothened with a planer. If the growth rings were not clearly visible, a chemical paint (termed as Clear Varnish in Nepal) and highly magnifying glass were used to better visualize them. Growth rings were marked and the radius from pith to each growth ring was precisely measured along the four perpendicular lines passing through pith to bark. Bark thickness was also measured. In four radial directions, total numbers of growth rings were counted and the radius was precisely measured at every second growth ring. Four measured radii were then averaged for each year. The age of a tree at stump height was assumed equal to the number of growth rings counted. Diameter growth was measured under bark, but it is normally measured over bark. Therefore, it was necessary to convert under bark diameter measurements to over bark diameters of the stumps.

Fig. 1. Study area

The mean stump diameters, which represent most of tree sizes in the tree population available in the study area, were calculated. A model describing the relationship between over bark diameters (*DOB*) and under bark diameters *(DUB*) was developed to predict over bark diameters. For this, various linear and non-linear models were fitted to the data and compared. The equation 1 showed the best performance:

$$DOB_i = b_1 + b_2 \times DUB_i + \varepsilon_i \qquad (1)$$

where:

DOB_i – diameter over bark (cm) of tree *i,*
DUB_i – diameter under bark (cm) of tree *i,*
b_1, b_2 – model parameters,
ε_i – unexplained variance, which is assumed to be independent and normally distributed with mean zero and constant variance.

Parameter estimates of this model are: b_1 = 1.88, b_2 = 1.062; R^2_{adj} = 0.996, *RMSE* = 0.811.

Using the bark model (Eq. 1), over bark basal area annual growth of the stump was calculated for each felled tree. Summary statistics of stump diameter data are presented in Table 1. A graph of basal area trajectories against age is presented in Fig. 2. The information on site quality (e.g. site index), stand characteristics (e.g. mean height, basal area, stem numbers), and variables describing competitive stress among indi-

Table 1. Summary of stump diameter data

Diameter class (cm)	Number of rings	Mean (cm)	Min (cm)	Max (cm)	SD (cm)
≤ 10	289	5.28	0.91	9.98	2.46
10–20	274	14.94	10.03	20.12	2.81
20–30	213	24.53	20.10	30.02	2.86
30–40	88	33.47	30.10	40.04	2.71
> 40	17	43.17	40.19	46.60	1.86

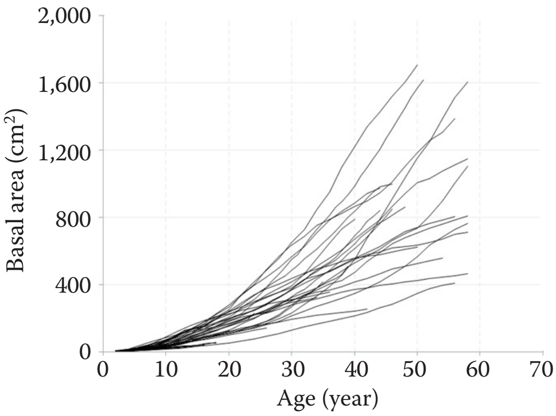

Fig. 2. Basal area growth trajectories

vidual trees were not available to this study. Therefore, the individual tree basal area growth models were developed using only age or diameter of the stumps as a single independent variable.

Modelling approach. A distance independent individual tree basal area growth model was developed within the limitations imposed by data, i.e. no variables describing competition, site quality, and tree positions were available to this study. The variables such as crown ratio or crown length might be included to better describe variations of basal area growth, but they were not measured either. Stump diameter and age of the trees were the only variables recorded for each tree. Therefore the individual tree basal area growth was modelled as a function of tree diameter or tree age without including spatial information. Thus, our growth models are distance independent. One of the advantages of distance independent models is that they allow for easy computation during application and rapid testing of various management alternatives (Vanclay 1994; Porte, Bartelink 2002).

Tree growth is an intrinsically exponential process at the early age, but at the later age, it is constrained by the action of two opposing forces such as external environmental resistance and internal self-regulatory mechanism (Zeide 1989, 1993). To describe growth processes properly, the terms which represent expansion and reduction of growth should be included in the models. The model possessing such properties can be derived from the integral form of mathematical functions by applying derivative rules (Zeide 1993). We chose a simple two-parameter based function, i.e. the von Bertalanffy function (Bertalanffy 1957), which is frequently applied in other studies to fit growth data. Realizing the fact that other three- or four-parameter based functions could lead to the computational complexities in an error-structured modelling approach (to be described later), we chose a simpler function (von Bertalanffy function). By the application of derivative rules (i.e. change of dimension with respect to time or size), we derived a differential model from the integral form of the von Bertalanffy function (see Zeide 1993). The integral and differential forms of this function are represented by Eq. 2 and Eq. 3, respectively.

$$y = a[1 - \exp(-bx)]^3 \quad (2)$$

$$\delta y = 3ab \times \exp(-bx)[1 - \exp(-bx)]^2 \quad (3)$$

when '$3ab$' and 'b' are substituted by b_1 and b_2, respectively, Eq. 3 turns out to be

$$\delta y = b_1 \times \exp(-b_2x)[1 - \exp(-b_2x)]^2 \quad (4)$$

where
y – size (total basal area),
x – diameter (size dimension) or certain period of time (age),
δy – basal area growth (increment),
a–b_2 – parameters of integral and differential functions, respectively.

Since this model (Eq. 4) cannot describe total variations of basal area growth, an error term, ε_i, was added to represent unexplained variations of basal area growth, and the model would appear as below.

$$\delta y = b_1 \times \exp(-b_2x)[1 - \exp(-b_2x)]^2 + \varepsilon_i \quad (5)$$

The autocorrelations existed between two or more consecutive measurements of diameters and ages of the same stump of a tree. Generally, the error term ε_i in Eq. 5 is assumed to be independent and normally distributed. However, this assumption does not hold for time series data, where residual errors from preceding and succeeding measurements have strong relationships (correlations). In order to reduce such correlations and secure the unbiased models, one should apply an autoregressive error-structured modelling approach (Cieszewski 2003; Greene 2003; Sharma et al. 2011). We applied this approach through expansion of the error term ε_i (in Eq. 5) into the first order error-structured model as below:

$$\varepsilon_i = \rho\varepsilon_{i-1} + e_i \quad (6)$$

where:
ρ – accounts for autocorrelation between current error and preceding error,
e_i – error term under the condition of independence and normality, also known as "white noise".

Then, Eq. 5 and Eq. 6 were combined together as below:

$$\delta y = b_1 \times \exp(-b_2x)[1 - \exp(-b_2x)]^2 + \rho\varepsilon_{i-1} + e_i \quad (7)$$

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Table 2. Parameter estimates and fit statistics of a model (Eq. 7), ($p > |t| = < 0.0001$)

Model type	Parameter	Estimates	Standard errors	t-value	*RMSE*	R^2_{adj}
Age dependent	b_1	161.3892	16.9412	9.53	5.0158	0.8668
	b_2	0.023413	0.00293	8.00		
	ρ	0.930592	0.0166	56.20		
Age independent	b_1	312.5964	51.8984	6.02	4.8494	0.8751
	b_2	0.01713	0.00272	6.31		
	ρ	0.880257	0.0215	40.96		

Model estimation and evaluation. Parameters of the model (Eq. 7) were estimated with nonlinear regression using PROC MODEL in SAS (SAS Institute Inc., Cary, USA). The fitted models were evaluated using goodness of fit statistics such as root mean squared error (*RMSE*), adjusted coefficient of determination (R^2_{adj}), and other criteria (Montgomery et al. 2001). Graphs of the residuals (individual residual series, mean residuals by size and age classes) and fitted curves overlaid on the observed data were also examined. Graphical analyses help to better understand the model's behaviour (Goelz, Burk 1992). This study did not consider the model validation by data splitting because of too small data set. Even though validation by data splitting does not provide much additional information as compared to goodness of fit statistics obtained directly from the model fitted to the entire data (Kozak, Kozak 2003), modellers usually prefer doing this unnecessarily. Nevertheless, validating models with new independent data is the best alternative only, but it costs much (Vanclay 1994). Resource limitations did not allow us to acquire new independent data and, therefore, validation is left open for future modellers.

RESULTS

Both age dependent and age independent individual tree basal area growth models were developed for Chir pine for one of the western districts, Rukum district, in Nepal. All parameter estimates including autocorrelation parameter estimates were

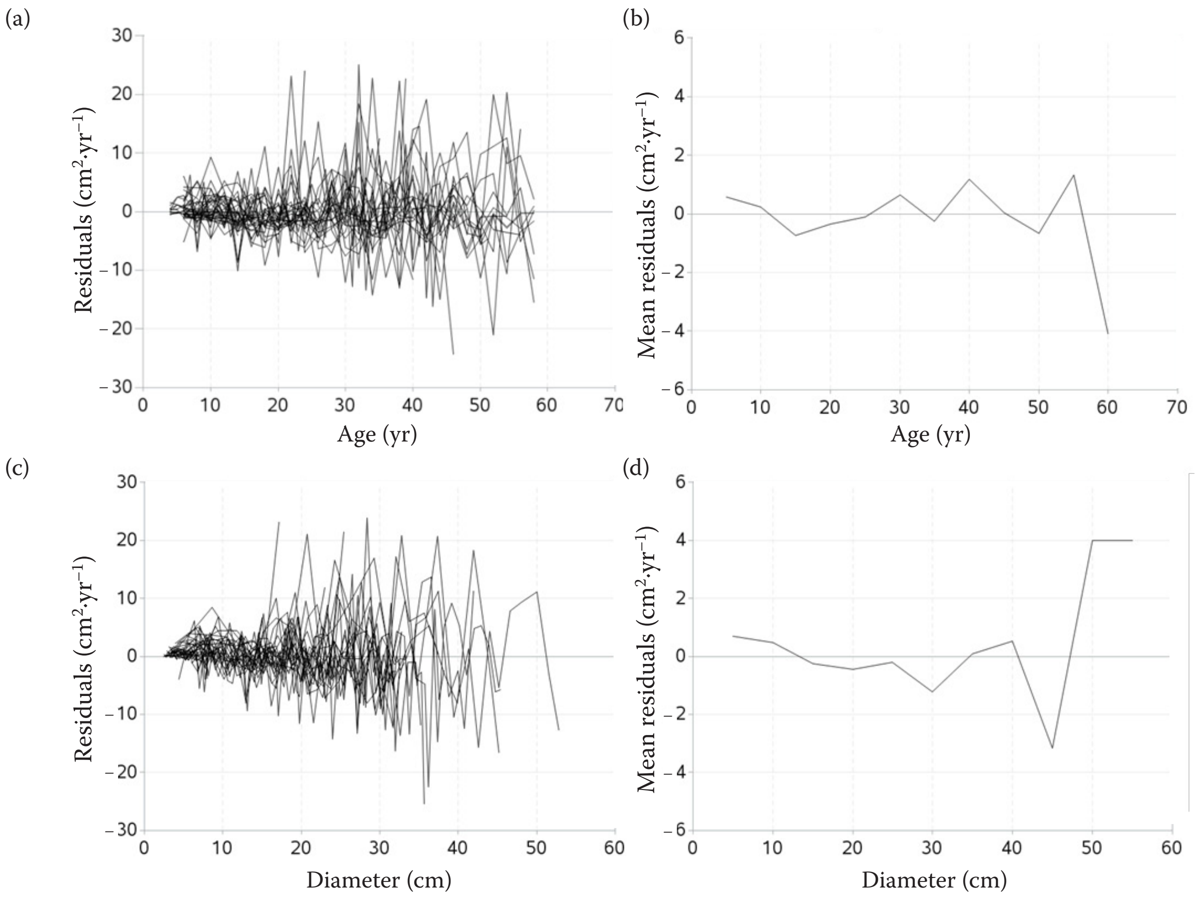

Fig. 3. Individual residual series and mean residuals by diameter and age classes

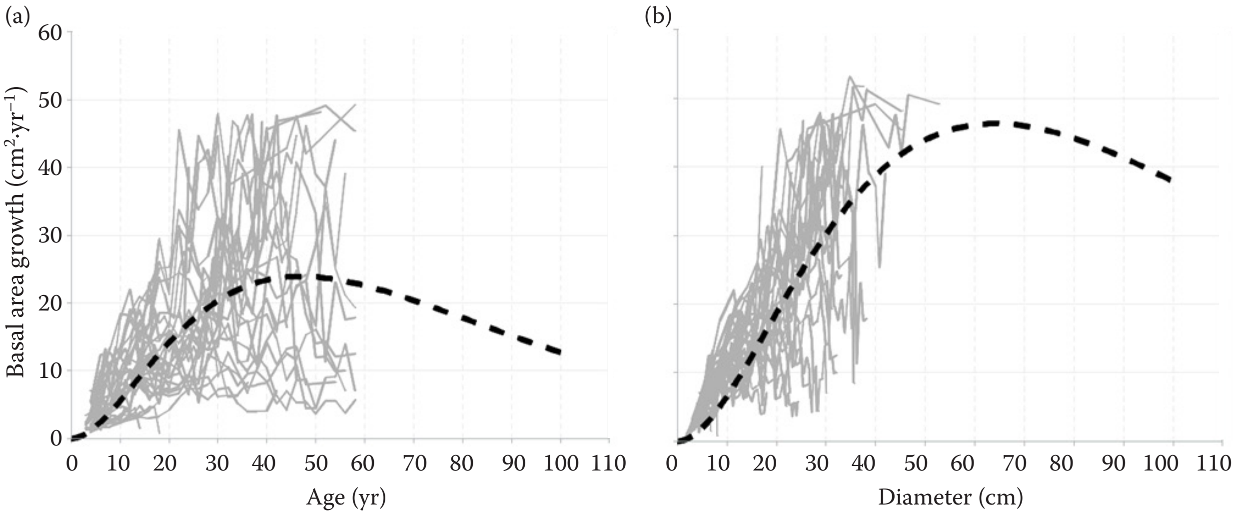

Fig. 4. Model curves overlaid on the observed basal area growth trajectories, the curves were produced with Eq. (7) using parameter estimates presented in Table 2

significant ($P < 0.01$) (Table 2). The age independent model showed relatively better fit statistics than its age dependent counterpart. A sawtooth-shaped individual tree residual series swirling around the zero line suggested that our model (Eq. 7) adequately fitted to the data across the observed age and diameter classes (Fig. 3). Mean residuals also showed no serious bias for trees of all size and age classes across the observed data range. No substantial heteroscedasticity problem was also observed in the residuals.

The basal area growth curves produced using parameter estimates (Table 2) showed that the highest growth rate (i.e. culmination) occurred when trees attained about 45 years of age or about 65 cm of stump diameter (Fig. 4). The basal area annual growth at the peak shown by an age independent model is higher than that shown by an age dependent model. The age dependent growth model showed a faster rate of increased or decreased basal area growth than the age independent model.

DISCUSSION

The description of most of the variations of basal area growth suggests that our chosen model (i.e. the von Bertanlaffy function) is adequately suited to the data. The decreased basal area growth shown by both model curves (Fig. 4) are not covered by our observed data. It is because that Chir pine trees of dbh larger than 40 cm are rarely available in the tree population as they are harvested by local forest users for construction purposes. Even though most of the model application data in the district will be available within a range of observed data, our models may be applied to the trees of slightly larger sizes than those that are not covered by the observed data. However, one should take precautions while extrapolating the models. Different growth rates and culminations shown by age dependent and age independent models (Fig. 4) are due to different ways of displaying basal area growth data. Because of the presence of few outlier observations in the data, larger residual deviations are present for older age and larger size classes (Fig. 2).

Faster and slower growth rates are biological phenomena. The tree growth is affected by several biotic and abiotic factors (Zeide 1993; Vanclay 1994; Pretzsch 2009; Vacek et al. 2009). These factors need to be modelled to adequately describe the growth pattern of individual trees. The effects of these factors are reflected in the individual tree and stand characteristics, which can be measured quantitatively. For example, the growth of a tree within the stand varies with stand density through the competitive stress imposed by its neighbouring trees, and this stress is described by a competition index (Pretzsch 2002; Hasenauer 2006; Pretzsch 2009; Sharma 2013). Thus, the effects of stand density are usually included in growth models with the application of either distance independent or distance dependent modelling approach (Wykoff 1990; Biging, Dobbertin 1992, 1995; Rivas et al. 2005; Pretzsch 2009). However, no stand density measure was available to this study. Without including any stand measure describing stand density (e.g. mean diameter, dominant diameter, basal area per hectare, stems per hectare, stand density index), site quality (e.g. site index) and competitive stress (e.g. competition index), our models described basal area growth data adequately well (Table 2, Fig. 3). Comparison of similar growth models developed by others is difficult, because the accuracy of the models depends on sample size, nature of data, species, and modelling methods applied. Generally, a proportion of the variations of basal area growth described by our models is higher than that described by basal area growth models developed elsewhere (Parresol 1995; Monserud, Sterba 1996; Schröder et al. 2002; Andreassen, Tomter 2003; Rivas et al. 2005; Pokharel, Froese 2009). These models include a number of stand and tree charactesistics as independent variables. Unlike others, we used stump analysis data, which provides better quality data than other data sources for modelling the radial growth of trees. The model with a single independent variable (e.g. diameter) is less expensive to measure and more practical than the models with other tree and stand variables included.

Our chosen model (Eq. 7) is simpler and computationally easier as it possesses only two parameters. An age independent model can be applied to both even-aged and uneven-aged stands. Whereas an age dependent model requires measurement of the stump age of each tree for the prediction of basal area growth, but getting accurate age for each tree, especially in the uneven-aged stands, is practically impossible. In such a condition, age independent model can be an appropriate option. Age independent model is thus recommended for practical application to both even-aged and uneven-aged stands. Even though the autocorrelation parameter of a model (Eq. 7) is significant ($P < 0.01$), it must be disregarded while applying this model. The autocorrelation parameter does not hold relevancy in model application. It only describes correlations between the repeated measurements made on the same stump. However, it is important to include autocorrelations in the model to reduce bias (Cieszewski 2003; Greene 2003; Sharma 2013). If autocorrelations were not accounted for, they would cause statistical complications and produce fit statistics that may be appealing, but not relevant (Huang, Titus 1995). Many others (Soares et al. 1995; Vanclay, Skovsgaard 1997; Kozak, Kozak 2003) believe that validation is an important part of modelling, because validation increases the credibility and confidence about the developed models. However, because of unavailability of new independent data, the models developed in this study were not validated and verified. More accurate basal area growth models can be expected through inclusion of some additional stand and tree characteristics such as competition index, site index, crown width and crown ratio as independent variables (Biging, Dobbertin 1992; Pretzsch 2002; Uzoh, Oliver 2008; Pretzsch 2009). When measurements of these characteristics of Chir pine forest are available, our models will be verified, validated, and recalibrated.

CONCLUSIONS

Two types of individual tree basal area growth models: age dependent and age independent, were developed for Chir pine for one of the western districts, Rukum district, in Nepal. Even though both model types adequately described data, the age independent model provided slightly better fit statistics, greater proximity to the observed values, and better residual distributions. Thus, the age independent model is recommended for practical application to both even-aged and uneven-aged stands, because this model requires only information of over bark diameter at 0.3 m above the ground. Follow-up works (i.e. recalibration, verification, and validation) on our models are recommended using data from all possible tree sizes, ages, site productivities, and stand conditions of Chir pine forest in the district.

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