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Centralblatt
für das gesamte
Forstwesen**Individual-based modelling for predicting height and biomass of juveniles
of *Shorea robusta*****Einzelbaumbasierte Modellierung zur Abschätzung der Höhe und
Biomasse von Jungbäumen von *Shorea robusta***Shes Kanta Bhandari¹*, Bir Bahadur Khanal Chhetri¹**Keywords:** *Allometry, tree growth, Nepal, community forestry, Wood density, regeneration***Schlüsselbegriffe:** *Allometrie, Waldwachstum, Nepal, Soziale Waldbewirtschaftung, Holzdichte, Verjüngung***Abstract**

Shorea robusta is one of the most widespread timber species in the forests of southern Nepal. Large parts of *Shorea robusta* forests of Nepal were degraded in the recent past due to policy conflict between the government and local users. After the introduction of community forestry, these forests have been regenerating gradually and the proportion of juvenile individuals in the forest is now very high. In the absence of biomass models of juvenile individuals, almost all forest inventories are neglecting the contribution of juvenile individuals in total carbon sequestration and storage. To close this knowledge gap, we developed a height and biomass prediction model for juvenile *Shorea robusta* in Nepal using an individual-based modelling approach. The models were calibrated with data from 110 destructively sampled trees and validated with 45 trees. We tested different model forms to select the best suited height and biomass prediction model. Once the best model form was selected, we

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calculated several models using different combination of predictor variables (i.e. tree diameter, tree height and wood density). Linear form (coefficient of determination R^2 0.80) for height and power form (R^2 0.89) for biomass prediction were selected as the best model forms. Product of diameter squared and height (R^2 0.91) and product of wood density, diameter squared and height (R^2 0.94) for the density-dependent model were the best predictors for biomass model. Due to different input data the predicted biomass by the models of this study differed substantially from biomass predictions using previously developed models of *Shorea robusta*. Thus, site- and size-specific models are required for accurate predictions of biomass and height of Juvenile of *Shorea robusta*. The model introduced here is site-specific and its application should be limited to conditions similar to this study.

Zusammenfassung

Shorea robusta ist eine weit verbreitete Baumart in den Wäldern im südlichen Nepal. Große Teile des *Shorea robusta* Waldes in Nepal wurden in der jüngsten Vergangenheit aufgrund politischer Konflikte zwischen der Regierung und lokalen Nutzern degradiert. Nach Einführung der kommunalen Forstwirtschaft haben sich diese Wälder allmählich verjüngt und der Anteil an Jungbäumen ist jetzt sehr hoch. Weil geeignete Modelle zur Vorhersage des Biomassezuwachses von Jungbäumen fehlen, vernachlässigen derzeit fast alle Waldinventuren den Beitrag der Jungbäume zur Kohlenstoffspeicherung. Um diese Wissenslücke zu schließen, haben wir ein auf Einzelbäumen basierendes Modell zur Schätzung der Wuchshöhe und Biomasse von jungen *Shorea robusta* aus Nepal entwickelt. Die Modelle wurden mit 110 destruktiv beprobten Jungbäumen kalibriert und 45 Bäumen validiert. Wir testeten verschiedene Varianten der Modelle, um das beste Modell zur Vorhersage von Wuchshöhe und Biomasse zu finden. Nachdem die beste Variante des Vorhersagemodells ausgewählt worden war, wurden mehrere Modelle mit unterschiedlichen Kombinationen der Prädiktorvariablen (Durchmesser, Baumhöhe und Holzdichte) entwickelt. Die beste Modellvariante war eine lineare Funktion (R^2 0.80) für die Höhe und eine Potenzfunktion (R^2 0.89) für die Biomasse. Das Produkt aus Höhe und Durchmesser zum Quadrat (R^2 0.91) und das Produkt aus Holzdichte, Höhe und Durchmesser zum Quadrat (R^2 0.94) waren die besten Modelle für die Biomasse. Die Modelle dieser Studie ergeben deutlich unterschiedliche Biomasse von *Shorea robusta* als die zuvor entwickelten Modelle. Es zeigt sich somit, dass standort- und größenabhängige Modelle wichtig sind für eine genaue Abschätzung der Biomasse von *Shorea robusta*. Unser Modell ist standortspezifisch und seine Anwendung sollte daher auf Bestände beschränkt werden, die den dieser Studie zugrunde liegenden ähnlich sind.

1. Introduction

Forest biomass is relevant for both forest productivity and climate change (Berndes et al., 2016; Kilpelainen et al., 2014). Regarding forest productivity, more biomass results in a higher yield, while regarding climate change, more biomass has a positive role in

minimizing the impact of climate change through sequestering a higher amount of atmospheric carbon dioxide (Chen et al., 2017). Accurate estimation of forest biomass is thus very important. Forest biomass consists of aboveground and belowground biomass (Nonini and Fiala, 2019). Empirical measurements of belowground biomass are time-consuming, costly and difficult, therefore, belowground biomass is often estimated using a constant proportion of aboveground biomass (Zhao et al., 2019; Addo-Danso et al., 2016). This study focusses on aboveground biomass at individual tree level. Aboveground biomass is measured using the direct or the indirect method. In the direct method, individual trees are felled destructively and weighed (Devi and Yadava, 2009; Ravindranath and Ostwald, 2008; Chung-Wang and Ceulemans, 2004). The direct method is more accurate, however, requires a large amount of time and resources (De Gier, 2003). The direct method is often used to develop allometric equations (i.e., an indirect method) that can be applied on larger areas and whole forests (Shrestha et al., 2018; Sharma et al., 2017; Navar, 2009; Segura and Kanninen, 2005). The indirect method estimates biomass without felling the individual trees and thus can be applied to larger forest areas. The indirect method can employ the shape, size (diameter, height), wood density in the form of allometric equations to predicted biomass (Ravindranath and Ostwald, 2008; Montes et al., 2000; Brown et al., 1989).

Allometric models establish a quantitative relationship between two or more variables (Klingenberg, 2016). The variable, that is more difficult to assess, is used as the dependent variable, while variables, that are easy to measure, are used as predictor variables. The allometric relationship is developed based on the accurate and detailed measurement on a small sample of typical individuals which are assumed to hold true for other individuals of a similar size and nature from the similar population. The application of allometric relationship enables estimation and prediction of different variables of individual trees and forest (Altanzagas et al., 2019; Daba and Soromessa, 2019). In published allometric models, tree height is predicted from stem diameter (Sharma, 2009; Huang et al., 1992) and biomass is predicted from stem diameter (Chapagain et al., 2014; Ong et al., 2004; Clough et al., 1997), stem diameter and height (Chapagain et al., 2014; Subedi and Sharma, 2012), stem diameter, height and wood density (Shrestha et al., 2018; Sharma et al., 2017). Most of the available biomass models were developed using data from large trees (Shrestha et al., 2018; Sharma et al., 2017; Nam et al., 2016; Huy et al., 2016; Clough et al., 2016; Chave et al., 2014; Paul et al., 2013; Blujdea et al., 2012; Subedi and Sharma, 2012; Navar, 2009; Chave et al., 2005; Tamrakar, 2000). Contribution of large-sized trees to biomass and carbon storage is high, but the contribution of juvenile (defined as a plant ≥ 30 cm in height and < 5 cm in diameter at 10 cm above ground surface) individuals is not negligible. Juvenile individuals can contribute around 5% biomass in forest depending on successional stage (Francis, 2000). Juveniles do not only contain biomass and carbon, but are also an important indicator of sustainability of forest management, reducing soil erosion and a predictor variable in analysing neighbourhood competition (Ter-Mikaelian and Parker, 2000). Despite their importance, few studies have focussed on juvenile trees. Chaturvedi et al. (2012) developed the multispecies bio-

mass model for 47 dry tropical woody species at the juvenile stage. Chapagain et al. (2014) developed allometric biomass models to estimate juvenile biomass of three tropical tree species (*Shorea robusta*, *Acacia catechu* and *Terminalia tomentosa*). BK et al. (2019) developed the allometric biomass model for juveniles of *Rhododendron arboreum* from the temperate region of Nepal.

Shorea robusta (C.F. Gaertn.) (family Dipterocarpaceae) is a large tree reaching 30-50 m height and 3-3.5 m diameter at breast height (dbh) (Chitale and Behera, 2012; Jackson, 1994). It is found across Nepal, India, Bangladesh and Myanmar (Gautam and Devoe, 2006; Stainton, 1972). In Nepal, it grows from 120 m to 1200 m elevation, but is more common at elevation lower than 800 m (Sah, 2000; Jackson, 1994). The contribution of *Shorea robusta* in total standing volume in Nepal is 19.28% (31.76 m³/ha) with a stem number of 65 trees per hectare (≥ 10 cm dbh), covering 15.27% of forest area (DFRS, 2015). These most recent estimate of standing volume, stem number and coverage of *Shorea robusta* are lower than the numbers reported in DFRS (1999). The different parts of *Shorea robusta* trees have been extensively used such as the stem as timber, construction material and fuelwood (Jackson, 1994), the leaves as fodder (Kibria et al., 1994) and dining plates (Kora, 2019), the resin as medicine of dysentery and gonorrhoea (Joshi, 2003).

Most of the *Shorea robusta* forest of Nepal was degraded in the recent past due to policy conflict between the government and local users (Sah, 2000; Land Resources Mapping Project, 1986). But after the introduction of community forestry system, these forests have been rejuvenated gradually (Paudel and Sah, 2015) and the proportion of the juvenile plants is high. Ample research in community forest (CF) of Nepal has demonstrated the positive impact of CF on forest conservation and regeneration (Bhattarai and Conway, 2008) and local livelihoods (Chhetri et al., 2012). Indeed, this positive effect has also raised the attention for estimating the biomass of juvenile plants to promote ecological sustainability in CF of Nepal. CF, one of the most successful participatory forestry programs implemented in Nepal, is joint venture of government and local user for conservation, protection, management and utilization for forest resources (Aryal et al., 2019; Nuberg, et al. 2019; Luintel et al., 2018). In Kankali CF (study area of this study), the average stand density of the CF is 7687 ha⁻¹ whereas stand density with trees >10 cm dbh is 572 ha⁻¹ and trees <10 cm dbh is 7115 ha⁻¹. The biomass and carbon measurement guideline of Nepal has recommended the allometric equation of Tamrakar (2000) ($\log \text{biomass} = a + b \log (\text{dbh})$) to estimate the biomass/carbon of plants having dbh <5 cm, although this equation was developed using few data from small-sized trees. This equation includes a large number of data from large sized trees and a small number of data from small sized trees. In the case of *Shorea robusta*, the equation was developed using the data ranging from 3 cm to 20 cm dbh (Tamrakar, 2000). Biomass and carbon estimation from the equation of Tamrakar (2000) might induce significant errors in the case of small-sized plants. Another model for estimation of juvenile biomass of three tropical tree species including *Shorea robusta* is developed by Chapagain et al. (2014) for western Nepal. The

model of Chapagain et al. (2014) was developed using the data from the three CFs in Bardiya district (28.3102° N and 81.4279° E) of province number five of Nepal (Figure 1). Even though, the study area of Chapagain et al. (2014) and the study area of this study lies on southern Nepal, the climate, physiography, stand density, site quality and human disturbance differs. The average annual precipitation of Bardiya district is 1118 mm (Chapagain et al., 2014) while the average annual precipitation of Chitwan district (study area of this study) is 1916 mm (DFO Chitwan, 2017). The altitudinal range of Bardiya district is 138 to 1279 m above mean sea level (Chapagain et al. 2014), while the altitudinal range of Chitwan district is 100 to 815 m above mean sea level. A model developed for a specific site may not be suitable for another site with different climate, physiography, stand density, site quality and human disturbance.

To minimize the error in biomass and carbon estimation, species-specific and size-specific equations including juvenile individual is required. Therefore this study aimed to develop allometric equation to predict height and biomass for juveniles of *Shorea robusta*. To achieve this aim, we selected the best form of the model out of several available height and biomass prediction models. In the case of biomass model, we further improved the model using the different combination of predictor variables. We further categorized the developed models into wood density-independent and wood density-dependent, to make our models easier applicable depending on the availability of predictor variables. We validated these developed models using a subset of data which was not used in the model development. We also compared our biomass models with the previously developed biomass models of *Shorea robusta*.

2. Materials and Methods

2.1 Study Area

The study was conducted in Kankali CF of Khairahani Municipality of Chitwan district Nepal (27.5291° N, 84.3542° E) (Figure 1). The forest coverage in the district is 63.25% (DFRS, 2015) and the 14.94% forest of the district is managed by 87 community forest user groups (CFUGs) in the form of CF including 43,313 households (DOF, 2017). The altitude of the district ranges from 100 m to 815 m above mean sea level. The average minimum and maximum temperature is 9.4 °C in January and 33.7 °C in June and average annual rainfall is 1916 mm (DFO Chitwan, 2017). The studied forest is 760 ha in area and has been managed by local CFUG since 1995. The CFUG is implementing different forest management activities like weeding, cleaning, climber cutting, pruning, thinning and other selective cutting. The forest type is natural and mixed in composition with *Shorea robusta* as dominant species. *Terminalia belerica*, *Terminalia tomentosa* and *Terminalia chebula* are other associate species of the forest. According to the operational plan, the CF has good quality stands and crown coverage is more than 65%. A part of this forest had been studied for carbon sequestration and a mo-

nitary value of carbon credit had been paid through a REDD+ pilot project in Nepal funded by a Norwegian development aid agency (NORAD) (Saito-Jensen et al., 2014).

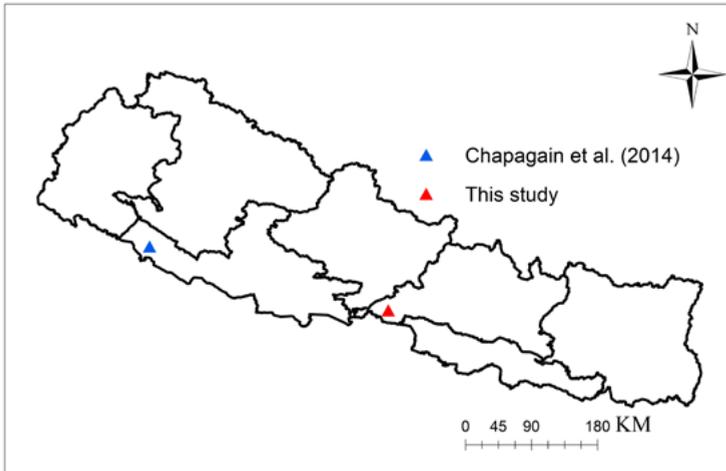


Figure 1: Map of Nepal showing the location of this study and the study site of Chapagain et al. (2014).

Abbildung 1: Karte von Nepal, die das Untersuchungsgebiet dieser Studie und das Untersuchungsgebiet der Studie von Chapagain et al. (2014) zeigt.

2.2 Sampling and Measurement

The operational plan of the CF was used to detect the variation in the size of the individuals of *Shorea robusta* (Operational Plan, 2019). 155 individual juveniles were selected purposively from the whole study area to represent existing variation of the site conditions, stand density, tree size (Chapagain et al., 2014; Adinugroho and Sidiyasa, 2006; Dorado et al., 2006; Edwards Jr et al., 2006). The individuals with a broken top, abnormal stem, diseased, dead and dying were excluded from measurement. We collected data on measured parameters (diameter, height, stem volume, total fresh weight of stem, branches and leaves, sample fresh weight of stem, branch and leaves) and derived parameters (total dry weight of stem, branch and leaves and wood density). Vernier Calliper (precision 1 mm) was used to measure the diameter of each juvenile at 10 cm above the ground level by following the method of Chapagain et al. (2014) and BK et al. (2019). Hereafter the diameter is referred as D . Then, the juvenile individual was felled by hand saw. Total height (H) was measured from base to tip of the juvenile using linear tape (precision 1 mm). A separate weight of stem, leaves and branches were recorded (precision 0.1 gram). At least 100 gram (g) of stem, lea-

ves and branches were weighed and placed in a labelled bag and transported to the laboratory as sample for oven dry weight. If a part (stem or branch or leaves) of the juvenile individual was less than 100 g, whole part was used for drying the samples. The fresh volume of the stem sample was determined using the principle of water displacement (BK et al., 2019; Shrestha et al., 2018; Chapagain et al., 2014; Chaturvedi and Khanna, 2011). The samples (leaves, branches, stem separately) were dried on an oven at 90°C till the constant weight was achieved to determine the dry weight of the sample. The weight of the samples was first recorded after 24 hours and then repeated at the interval of 12 hours. The wood density (ρ) was determined as the ratio of the dry weight of stem sample and its fresh volume (Equation 1). The total dry weight of leaves, branches and stem was determined using the ratio of dry weight and fresh weight of samples of leaves, branches and stem respectively. The total dry biomass of each juvenile individuals was calculated by adding the dry biomass of leaves, branches and stem. The descriptive statistics of the data used for modelling is given in Table 1.

$$\text{Wood density } (\rho) = \frac{\text{oven dry weight of sample}}{\text{fresh volume of sample}} \quad 1$$

Table 1: Descriptive statistics of the variables used for modelling the juvenile aboveground biomass of *Shorea robusta*.

Tabelle 1: Zusammenfassung der *Shorea robusta* Jungbäume, die für die Modellierung der oberirdischen Biomasse verwendet wurden.

Diameter class (cm)	Variables	Mean \pm Standard deviation (range)
0-1	Diameter (cm)	0.502 \pm 0.172 (0.2-0.91)
	Height (m)	0.79 \pm 0.29 (0.33-1.49)
	Wood density (g cm ⁻³)	0.29 \pm 0.08 (0.05-0.47)
	Biomass (g)	15.10 \pm 11.58 (1.30-45.33)
	Number	40
1-2	Diameter (cm)	1.39 \pm 0.28 (1.00-1.97)
	Height (cm)	1.53 \pm 0.35 (0.91-2.62)
	Wood density (g cm ⁻³)	0.38 \pm 0.07 (0.20-0.53)
	Biomass (g)	91.59 \pm 50.08 (33.66-259.69)
	Number	38
2-3	Diameter (cm)	2.52 \pm 0.28 (2.09-2.94)
	Height (cm)	2.10 \pm 0.56 (1.25-4.07)
	Wood density (g cm ⁻³)	0.46 \pm 0.11 (0.30-0.71)
	Biomass (g)	354.14 \pm 164.11 (129.23-918.14)
	Number	26
3-4	Diameter (cm)	3.51 \pm 0.27 (3.09-3.96)
	Height (cm)	3.16 \pm 0.73 (1.88-4.77)
	Wood density (g cm ⁻³)	0.49 \pm 0.07 (0.38-0.64)
	Biomass (g)	875.83 \pm 432.66 (403.12-2005.19)
	Number	23
4-5	Diameter (cm)	4.48 \pm 0.30 (4.02-4.96)
	Height (cm)	3.63 \pm 0.86 (2.11-5.55)
	Wood density (g cm ⁻³)	0.49 \pm 0.09 (0.25-0.68)
	Biomass (g)	1563.33 \pm 518.14 (883.61-2630.12)
	Number	28
Total 0-5	Diameter (cm)	2.22 \pm 1.48 (0.20-4.96)
	Height (cm)	2.06 \pm 1.19 (0.09-5.55)
	Wood density (g cm ⁻³)	0.41 \pm 0.11 (0.05-0.71)
	Biomass (g)	499.06 \pm 643.18 (1.30-2630.12)
	Number	155

2.3 Modelling approach

We fitted different forms of models including linear, logarithmic, inverse, quadratic, power, sigmoid and exponential (Table 2) to our data to select the best height and biomass prediction models. For height prediction, we fitted the models with height

as the dependent variable and diameter as the predictor variable. For biomass prediction, we fitted the models with biomass as the dependent variable and diameter as the predictor variable. The parameters and fit statistics for each model were estimated in R using the `lm`, `nls` and `nlsLM` function in the `minpack.lm` package (R Core Team, 2017), and evaluated using different criteria including significance of estimated parameters (at 5% level of significance); coefficient of determination (R^2 ; higher values indicate better models); root mean squared error (RMSE; lower values indicate better models) (Montgomery et al., 2001); and Akaike Information Criterion (AIC; lower values indicate better models) (Akaike, 1972; Burnham and Anderson, 2002). Distribution of residuals was also considered in selecting the best model.

Table 2: Different forms of models and their equations used in height and aboveground biomass modelling of juveniles of *Shorea robusta* (Y is dependent variable and X is predictor variable).

Tabelle 2: Modellformen und Gleichungen, die bei der Modellierung der Wuchshöhe und der oberirdischen Biomasse von Jungbäumen der *Shorea robusta* verwendet wurden (Y ist abhängige Variable und X Prädiktorvariable).

Model form	Equation
Linear	$Y = \alpha_1 + \alpha_2 X + \varepsilon_{ij}$
Logarithmic	$Y = \alpha_1 + \alpha_2 \log(X) + \varepsilon_{ij}$
Inverse	$Y = \alpha_1 + \frac{\alpha_2}{X} + \varepsilon_{ij}$
Quadratic	$Y = \alpha_1 + \alpha_2 X + \alpha_3 X^2 + \varepsilon_{ij}$
Power	$Y = \alpha_1 X^{\alpha_2} + \varepsilon_{ij}$
Sigmoidal	$Y = \exp\left(\alpha_1 + \frac{\alpha_2}{X}\right) + \varepsilon_{ij}$
Exponential	$Y = \alpha_1 \exp(\alpha_2 X) + \varepsilon_{ij}$

Once the best form of biomass model was selected, a different combination of predictor variables was used in that form of biomass model. The different combinations of predictor variables used were diameter alone (D), product of diameter and height (DH), product of square of diameter and height (D²H), product of wood density, diameter and height (ρ DH) and product of wood density, square of diameter and height

(ρD^2H) (BK et al., 2019; Shrestha et al., 2018; Chapagain et al., 2014).

2.4 Validation

The whole data ($n = 155$) was split into calibration data ($n = 110$) and validation data ($n = 45$). The validation data was used in the best-selected model to analyse the model performance. We estimated the correlation coefficients between the predicted values and observed value of validation data. Correlation coefficient was categorized as very high (>0.9), high (0.7-0.9), moderate (0.5-0.7), low (0.3-0.5) and negligible (0-0.3) (Mukaka, 2012). Plots of predicted versus observed values were also generated to evaluate whether the model prediction is similar to observed data or not. Furthermore, we used a paired sample t-test to test whether there was a significant difference between observed and predicted values at 5% level of significance.

2.5 Comparison of validated models with previously developed biomass models

We compared our biomass models with two categories of previously developed biomass models. The first category of models was biomass prediction models of juvenile individuals of *Shorea robusta*. Chapagain et al. (2014) had developed eight biomass models for juvenile individuals of three tropical tree species including *Shorea robusta* in Nepal. We compared our models (based on D , D^2H and ρD^2H) with three models of Chapagain et al. (2014) (Equation 2, 3 and 4) which predicts the biomass of *Shorea robusta* based on D , D^2H and ρD^2H .

$$\text{Biomass (g)} = 71.9320 D^{(1.6991+0.0585 D)} \quad 2$$

$$\text{Biomass (g)} = \exp(4.1580 (D^2H)^{0.1380}) \quad 3$$

$$\text{Biomass (g)} = \exp(4.4790 (\rho D^2H)^{0.1322}) \quad 4$$

Where D is diameter (cm) measured at 10 cm above the ground level, H is total height (m) and ρ is wood density (g cm^{-3}).

The second category of models were biomass prediction models of large sized trees of *Shorea robusta*. Sharma and Pukkala (1990) (Equation 5, 6), Tamrakar (2000) (Equation 7) and Subedi (2017) (Equation 8, 9) had developed biomass models for *Shorea robusta* in Nepal. These models were based on dbh (cm) and/or height (m) of the *Shorea robusta*, however, our models were based on diameter at 10 cm above the ground level and height. We developed a simple power function model to predict the dbh from the diameter at 10 cm above the ground level (Equation 10).

$$\ln(\text{Volume}) = -2.4554 + 1.9026 \ln \text{dbh} + 0.8352 \ln \text{height} \quad 5$$

$$\text{Biomass (Kg)} = \text{Volume} * 880 \quad 6$$

$$\ln(\text{biomass}) = a + b \ln(\text{dbh}) \quad 7$$

$$\ln(\text{Volume}) = -8.04674 + 2.26641 \ln \text{dbh} \quad 8$$

$$\text{Biomass (Kg)} = \text{Volume} * 880 \quad 9$$

$$\text{dbh} = 0.7031 D^{0.9527} \quad 10$$

Where dbh is diameter at breast height at 1.3 m above ground (cm) and D is diameter (cm) at 10 cm above the ground level.

For comparison, we predicted the biomass using the models of Chapagain et al. (2014), Sharma and Pukkala (1990), Tamrakar (2000), Subedi (2017) and the models developed in this study. Then we plotted the predicted biomass against the predictor variables (Figure 5). Paired sample t-test was used to test whether the predicted biomass by the model of this study and other previously developed models was same. Correlation coefficient (r) was used to evaluate the relationship between the models developed in this study and each of the previously developed models.

3. Results

The result showed that the stem, leaf and branch biomass of juvenile individual covers 83%, 11% and 6% of total biomass respectively. Leaf and branch biomass of juvenile covers 12% and 7% of total stem biomass. Similarly, branch biomass of juvenile covers 57% of leaf biomass.

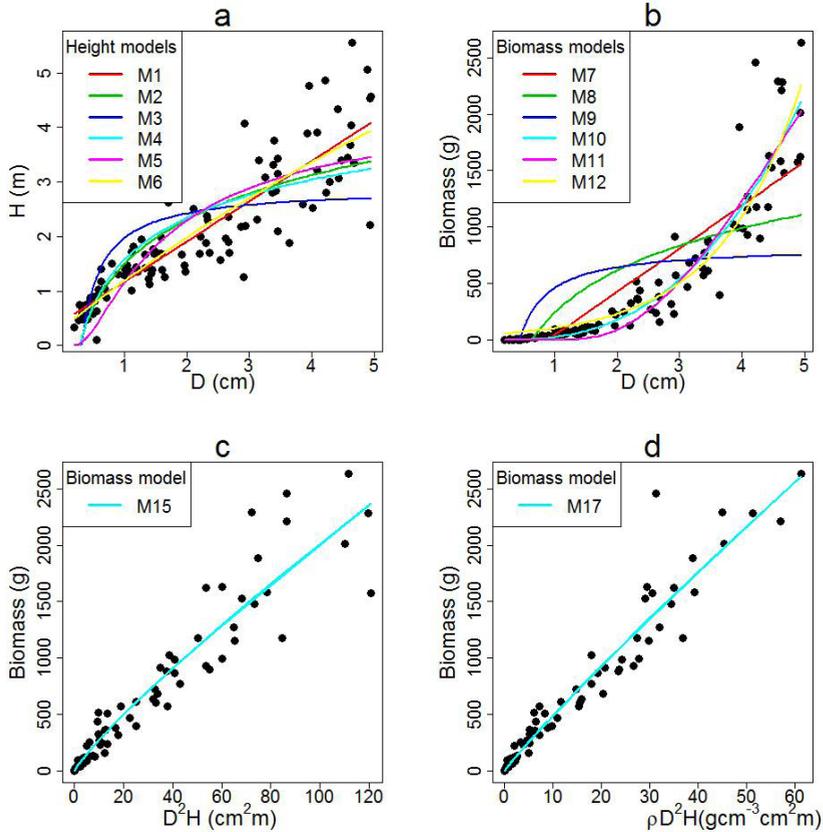


Figure 2: Model predictions of *Shorea robusta*; (a) tested tree height models, (b) tested aboveground biomass models, (c) best performing biomass model using diameter at 10 cm above ground (D) and tree height (H) and (d) best performing biomass model using D , H , and wood density (ρ).

Abbildung 2: Modellschätzungen von *Shorea robusta*; (a) getestete Baumhöhen-Modelle, (b) getestete Biomasse-Modelle, (c) bestes Biomasse-Modell unter Verwendung des Durchmessers 10 cm über dem Boden (D) und der Baumhöhe (H) und (d) bestes Biomasse-Modell unter Verwendung von D , H und Holzdicke (ρ).

3.1 Model for height prediction

All model parameters were significant at a 95% confidence interval except one parameter of the quadratic form of the model ($p = 0.59$), which we excluded from further analysis. The inverse form of the model only described 49% of the variation in total height with highest RMSE and AIC than other models (Table 3). Logarithmic form of model overestimated the height for smaller juveniles and underestimated for larger juveniles, however, the sigmoidal model underestimated the height for smaller ju-

veniles and overestimated the height of larger juveniles (Figure 2a). The exponential model overestimates the height for smaller juveniles (Figure 2a). Linear and power form of the model described more than 80% of the variation in total height. Furthermore, the linear and power form of the model produced smaller RMSE and AIC than other models. Out of the remaining two models, the linear model described higher variability in height with a lower RMSE and AIC than the power model (Table 3). Figure 3a showed negligible curvature and outliers while plotting the unstandardized residuals against the predicted height. The absence of curvature and outlier in the linear model suggests the absence of local bias. Thus, we selected the linear model (M1, Table 3) for predicting height from the diameter, though the difference of fit statistics between the linear model and power model was very small.

Table 3: Tested height models with equation and coefficients, their respective coefficient of determination R^2 , root mean square error (RMSE) and Akaike's Information Criterion (AIC) used diameter for juvenile *Shorea robusta*. H is tree height and D tree diameter 10 cm above ground.

Tabelle 3: Getestete Baumhöhen-Modelle, deren Gleichungen und Koeffizienten mit jeweiligen Bestimmtheitsmaß R^2 , RMSE und AIC unter Verwendung des Durchmessers von *Shorea robusta* Jungbäumen (H ist die Höhe und D der Stammdurchmesser).

	Model form	Equation	R^2	RMSE	AIC
M1	Linear	$H = 0.42 + 0.73 D$	0.80	0.53	178.95
M2	Logarithmic	$H = 1.49 + 1.17 \log D$	0.72	0.64	219.02
M3	Inverse	$H = 2.88 - \frac{0.91}{D}$	0.49	0.87	284.48
M4	Power	$H = 1.17 D^{0.75}$	0.80	0.54	182.13
M5	Sigmoidal	$H = \exp\left(1.51 - \frac{1.37}{D}\right)$	0.70	0.66	224.82
M6	Exponential	$H = 0.88 \exp(0.32 D)$	0.78	0.56	190.50

3.2 Model for biomass prediction

We employed similar criteria like height prediction model to select the best biomass prediction model. The parameter estimates of the quadratic model were non-significant ($p = 0.06$) at a 95% confidence interval and therefore excluded from further processing. The inverse and logarithmic models describe low variability in biomass of

juveniles (Table 4). Linear model overestimated the biomass for smaller juveniles and underestimated for larger juveniles (Figure 2b). The sigmoid model underestimated and exponential model overestimated the biomass for smaller juveniles (Figure 2b). The power model described higher variability in biomass of juveniles with minimum RMSE and AIC than other models (Table 4). Thus, power model was selected for predicting biomass of juveniles, though the difference in fit statistics among the power, sigmoid and exponential models was very small.

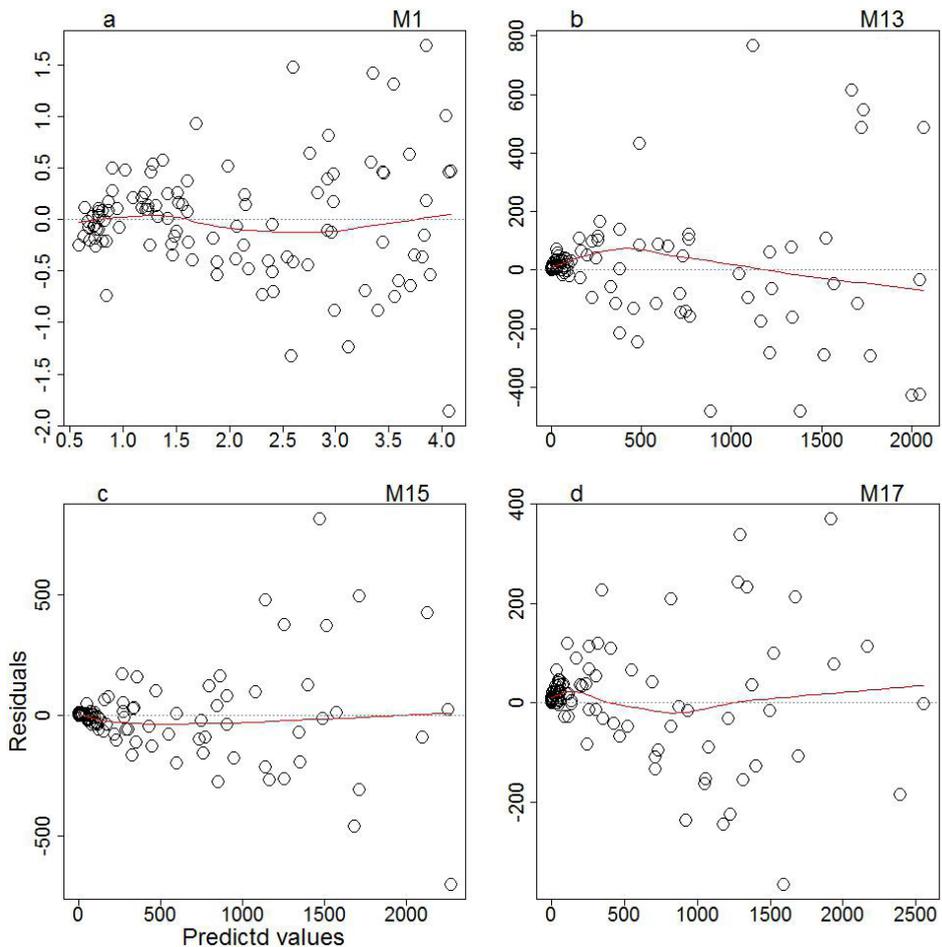


Figure 3: Distribution of residuals for four selected models for *Shorea robusta*, M1 predicts tree height, M13, M15 and M17 predicts aboveground biomass.

Abbildung 3: Verteilung der Residuen für vier ausgewählte Modelle für *Shorea robusta*, M1 prognostiziert die Baumhöhe, M13, M15 und M17 prognostizieren die oberirdische Biomasse.

Table 4: Tested biomass models with equation and coefficients, their respective coefficient of determination R^2 , root mean square error (RMSE) and Akaike's Information Criterion (AIC) used diameter for juvenile *Shorea robusta*. B is tree biomass and D tree diameter 10 cm above ground.

Tabelle 4: Getestete Biomasse-Modelle, deren Gleichungen und Koeffizienten mit jeweiligen Bestimmtheitsmaß R^2 , RMSE und AIC unter Verwendung des Durchmessers von *Shorea robusta* Jungbäumen (B ist die Biomasse und D der Stammdurchmesser).

	Model form	Equation	R^2	RMSE	AIC
M7	Linear	$B = -338.02 + 382.81 D$	0.77	305.81	1560.91
M8	Logarithmic	$B = 242.31 + 541.31 \log D$	0.54	434.91	1638.70
M9	Inverse	$B = 827.51 - \frac{364.75}{D}$	0.28	550.14	1688.93
M10	Power	$B = 26.89 D^{2.72}$	0.89	214.71	1483.81
M11	Sigmoidal	$B = \exp\left(9.70 - \frac{10.34}{D}\right)$	0.88	221.58	1490.68
M12	Exponential	$B = 50.53 \exp(0.76 D)$	0.88	222.70	1491.78

We also examined the power form of the model using a different combination of predictor variables to optimize the predictive capacity of the model (Table 5). The estimated parameters for five different categories of the power model were significant. In density-independent categories, the model with D^2H demonstrates the highest R^2 , lowest RMSE and AIC than others. On the other hand, the model with ρD^2H as predictor variable demonstrates the best fit (highest R^2 , lowest RMSE and AIC) in the group of density-dependent models (Table 5). The unstandardized residuals against the fitted values with a smooth superimposed curve for power model of biomass prediction (M13, M15 and M17) is presented in Figure 3b,c,d. Here we examined for evidence of curvature and outliers. The graph of power model (M13, M15 and M17) showed minimum error in M17 with negligible curvature and outliers. The absence of curvature in these models suggests the absence of local bias in the model. Overall, the model (M17) with the inclusion of wood density in the predictor variable (ρD^2H) best described the variations in biomass of juveniles of *Shorea robusta*. The curve of the model M15 and M17 overlaid on the observed data showed a good match to the data (Figure 2c, d).

Table 5: Variables and the estimated coefficients used for biomass models of juveniles of Shorea robusta in power form with their respective R^2 , RMSE and AIC (D is stem diameter, H height and ρ wood density).

Tabelle 5: Variablen und die geschätzten Parameter der Biomasse-Modelle von Jungbäumen der *Shorea robusta* der Potenzform mit jeweiligen R^2 , RMSE und AIC (D ist der Stammdurchmesser, H Höhe und ρ Holzdichte).

	Variables	a	b	R^2	RMSE	AIC	Rank
M13	D	26.89	2.72	0.89	214.71	1483.81	V
M14	DH	52.72	1.18	0.90	205.02	1473.75	IV
M15	D^2H	37.50	0.86	0.91	184.44	1450.69	III
M16	ρDH	119.84	1.21	0.92	176.59	1441.20	II
M17	ρD^2H	60.05	0.91	0.94	148.84	1403.94	I

3.3 Validation

By using the generated models for prediction of height (M1, Table 3) and biomass (M13, M15 and M17, Table 5), we executed prediction runs based on the validation dataset. The correlation coefficients between observed and predicted height was high ($r = 0.87$) (Figure 4a) and between observed and predicted biomass was very high ($r = 0.91$ to 0.97) (Figure 4b, c, d). The paired sample t-test showed that the observed and predicted values of height (Figure 4a) and biomass (Figure 4b, c, d) did not differ statistically ($p > 0.05$).

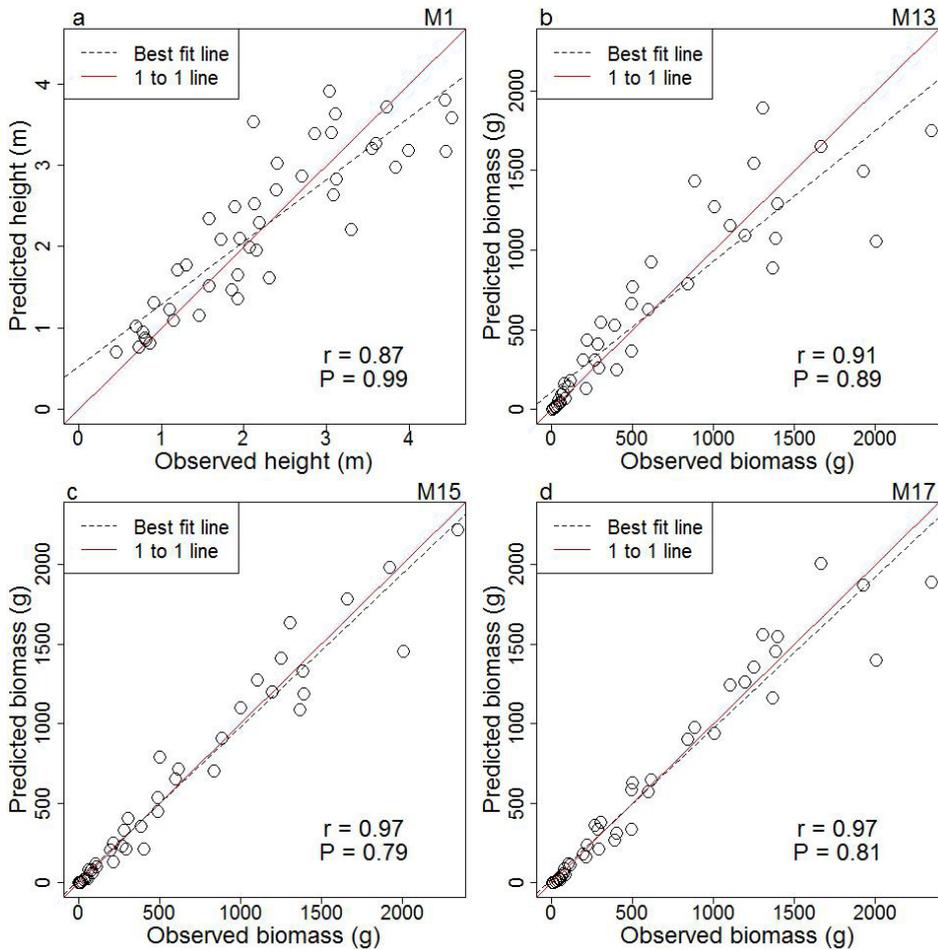


Figure 4: Relationships of observed and predicted values of four selected models of *Shorea robusta* (r = correlation coefficient and p = p -value); (a) model M1 predicts height from diameter; (b) model M13 aboveground biomass based on diameter only; (c) model M15 predicts biomass prediction model using product of diameter square and height; (d) model M17 predicts biomass prediction model from product of wood density, diameter squared and height.

Abbildung 4: Zusammenhang zwischen beobachteten und geschätzten Werten ausgewählter Modelle von *Shorea robusta* (r = Korrelationskoeffizient und p = p -Wert); (a) M1 Modell berechnet Höhen mit Durchmesser; (b) M13 Modell berechnet Biomasse ausschließlich mit Durchmesser; (c) M15 Modell berechnet Biomasse aus dem Produkt von Höhe und Durchmesser zum Quadrat; (d) M17 Modell berechnet Biomasse aus dem Produkt von Holzdicke, Höhe und Durchmesser zum Quadrat.

3.4 Comparison of validated models with previously developed biomass models

Juvenile biomass predicted by the model of this study (M13, M15 and M17) and the previous models of Sharma and Pukkala (1990), Tamrakar (2000), Chapagain et al. (2014) and Subedi (2017) showed a higher degree of positive correlation ($r = 0.97$ to 0.99). The predicted biomass by the model of this study (M13, M15 and M17) was significantly different ($p < 0.05$) with the predicted biomass of each of the previous models except one model of Chapagain et al. (2014) which is based on D ($p = 0.08$) (Equation 2).

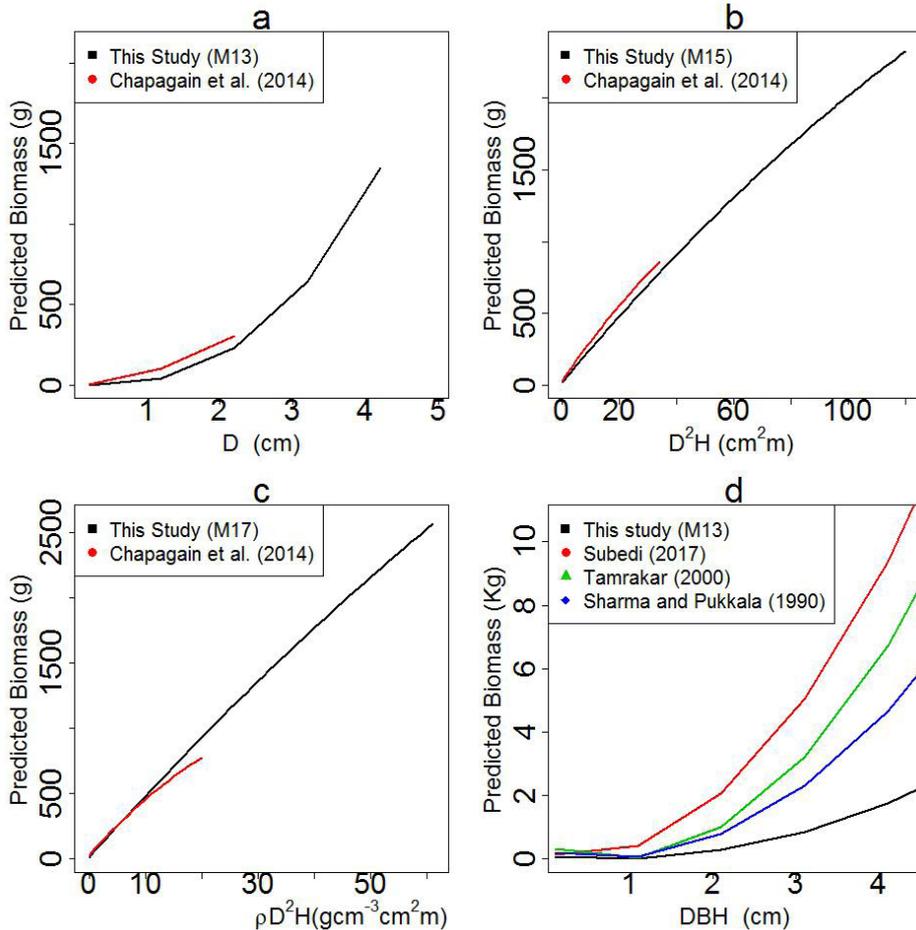


Figure 5: Comparison of the models introduced in this study with published models of *Shorea robusta* with different combinations of predictor variables (D, D²H, ρD²H, dbh) (a) biomass models based on diameter 10 cm above ground (D) only; (b) biomass models based on product of diameter squared and height only; (c) biomass models based on product of wood density, diameter squared and height; (d) biomass model based on diameter at breast height (dbh) (M13 has power form using the predicted dbh in cm and biomass in kg).

Abbildung 5: Vergleich unserer Modelle mit früheren Modellen der *Shorea robusta* mit verschiedenen Kombinationen von Prädiktorvariablen (D, D²H, ρD²H, dbh) (a) Biomasse-Modelle, die nur Durchmesser (D) verwenden; (b) Biomasse-Modelle, die auf dem Produkt von Höhe und Durchmesser zum Quadrat basieren; (c) Biomasse-Modelle, die auf dem Produkt von Holzdichte, Durchmesser zum Quadrat und Höhe basieren; (d) Biomasse-Modelle, die den Durchmesser in Brusthöhe (dbh) verwenden (Modell M13 ist die Potenzfunktion mit geschätztem dbh in cm und Biomasse in kg).

4. Discussion

This study showed the best performance of a liner model (M1) in diameter-height allometry. This result is inconsistent with the results of Sharma (2009) and Thapa et al. (2013), who reported a non-linear relationship in diameter-height allometry. As the growth in diameter and height is linear in nature during the juvenile stage of individual trees, the linear function may have explained a higher amount of variation in height. As the individual tree increases in age, the growth in height speed up until the individual trees reached the middle stage (Chaturvedi and Khanna, 2011), however, there will be less growth in diameter. As the individual trees reach the middle stage, the height growth tends to decrease and diameter growth tends to increase. The different rates of growth of individual tree at different stages of life introduced a non-linear relationship between diameter and height. The non-linear relationship of diameter-height allometry in large-sized individual trees has been well established (Deng et al., 2019; Ng'andwe et al., 2019; Subedi et al., 2018; Khadka et al., 2015).

Similar to studies (BK et al., 2019; Kebede and Soromessa, 2018; Sharma et al., 2017; Shrestha et al., 2018; Pastor et al., 1984), we found a simple power function as the best form of the model to predict the aboveground biomass of juvenile individual of *Shorea robusta*. Biomass of individual trees correlates non-linearly with individual tree variables, however, the form of non-linearity differs with species, stand density, site index, geographic regions and climate (Luo, 2020; Xing et al., 2019; Nam et al., 2016; Chave et al., 2014; Chapagain et al., 2014; Chave et al., 2005).

Biomass of individual trees is the sum of the biomass of stem, branches and foliage, however, a major portion of the biomass is contributed by stem of the individual trees (Ketterings et al., 2001). Therefore a number of biomass prediction models have found diameter as the best predictor variable (Pastor et al., 1984), which is not consistent with the result of this study. We found weakest performance while using diameter alone (M13) in the biomass prediction model (Table 5) compared to the models which uses diameter, height and wood density. As individual juveniles having the same stem diameter may vary in height, they may also vary in biomass. Therefore, the model with diameter and height as the predictor variables explained more variation in biomass. We observed this in our study as the model M14 and M15 performed better than model M13 which is consistent with many other studies (Xing et al., 2019; Kebede and Soromessa, 2018; Shrestha et al., 2018; Nam et al., 2016). As the individual juveniles having the same stem diameter and height may vary in wood density, they may also vary in biomass. Therefore, the model with diameter, height and wood density as the predictor variables explained more variation in biomass (Shrestha et al., 2018; Alvarez et al., 2012; Chaturvedi et al., 2012). This was also proved in our study as the model M16 and M17 performed better than model M13, M14 and M15. The model M17 performed best from the group of density-dependent models. The wood density does not improve the model always for example, Chapagain et al. (2014) found that the model with diameter and height better than the model with

diameter, height and wood density. We tested slenderness coefficient as predictor variable, however, it did not improve the model. Our models which were developed using ordinary least square regression showed a good fit to the data, however, there is still possibility of improving these models using mixed effect modelling approach. We could not use mixed effect modelling approach because the data were collected only at one time using individual juveniles selected purposively.

Model validation is one of the important step in the development of models as it increases the credibility and confidence about the predictive capacity of the models (Soares et al., 1995; Vanclay and Skovsgaard, 1997). A high ($r=0.87$) to very high ($r=0.97$) correlation coefficients between observed and predicted values suggested that our models are well validated (Figure 4). This validation was further supported by non-significant difference at a 95% confidence interval in paired sample t-test. It shows that the models selected in this study are capable to predict as accurately as field-measured biomass.

Biomass predicted by model of this study (M13) and Chapagain et al. (2014) using D as predictor variable (Equation 2) did not differ significantly, however, the biomass predicted by the model of this study (M15, M17) and Chapagain et al. (2014) using D^2H and ρD^2H as predictor variables (Equation 3, 4) differed significantly. The reason behind this difference may be the high variation in height and wood density of the juveniles that are growing in two different geographical areas thus, differences in the stand density, site quality, topography and climate. The average and range values of height and wood density of juveniles used in this study was higher than those used in Chapagain et al. (2014). The differences in predicted biomass was small for smaller juveniles, however, difference increased with an increase in values of predictor variable (Figure 5b, c).

As expected, the predicted biomass by our model (M13) and predicted biomass by previous models of Sharma and Pukkala (1990), Tamrakar (2000) and Subedi (2017) showed a significant difference ($p<0.05$) (Figure 5d). Two reasons may explain these differences. The first reason may be the differences in the size of the trees used in the model development. Our study used juvenile individuals of *Shorea robusta* ($D = 0.20$ cm to 4.96 cm) while Sharma and Pukkala used larger sized individuals of *Shorea robusta* ($dbh = 12.70$ cm to 144.50 cm). The dbh of *Shorea robusta* trees used in the model of Subedi (2017) ranged between 30.10 cm to 108.50 cm. The second reason may be the extent of area covered during sample data collection. The data for Sharma and Pukkala (1990) was collected from the whole range of distribution of *Shorea robusta* whereas the data for Subedi (2017) was collected from two districts (Kailali and Kanchanpur) of far western Nepal. The data for the present study was collected from the one community forest of Chitwan district of central Nepal.

As the altitudinal, climatic and species variation is very high in Nepalese forest, a universal model for all size, site and species is not suitable. The model developed from

the data of large sized individual may not predict the biomass of small sized individual and the model developed from one site of the country may not be suitable in another site. Therefore, new models that are size specific, site specific and species specific are required for accurate prediction of individual tree biomass.

Data collected using destructive sampling method were used to develop the models and the number of juvenile individuals used ($n=155$) in this study was larger than those used in other studies (BK et al., 2019; Shrestha et al., 2018; Subedi and Sharma, 2012; Sharma, 2011) which ranged from 27 to 66 individuals. Data from smaller number of sampled trees have also performed good results in biomass model development if they have been collected from destructively sampled trees representing potential sources of variation. The large-sized individual showed relatively high residuals, however, the overall distribution of residual was random (Figure 3). Similar trend of residuals have also been observed by Bk et al. (2019). The absence of systematic trend or bias in the residuals also confirms the higher degree of precision in our models. The precision of the model have also been proved from the validation of the models (Figure 4). The models developed in this study are applicable to a variety of predictor variables. For example, the biomass model is applicable if only the diameter is available, or diameter and height is available or diameter, height and wood density is available. The models with wood density provide higher precision, however, require more resources and time to determine wood density.

The direct application of the models developed in this study is to predict and estimate the height and biomass of juvenile individual of *Shorea robusta*. These models may help to minimize the lack of biomass models for the juvenile stage which has caused a substantial underestimation of the total biomass and carbon in forests. The models may contribute to adding the economic value of carbon trading from juvenile individuals. Prediction and estimation of biomass of juvenile individuals are used in quantification of forest fuels, assessing the potential of young stands as a fibre source and indicating net primary production (Wagner and Ter-Mikaelian, 1999). The juvenile individual biomass may be used as a response variable in evaluating the impact of neighbourhood competition (Ter-Mikaelian and Parker, 2000). In addition to these applications, juvenile individuals play an important role in balancing forest ecosystems.

5. Conclusions

Among several forms of the model tested, a linear form for height prediction and power form for biomass prediction performed better than other forms of the model. Different combinations of predictor variables further improved the biomass model. Product of square of diameter and height ($R^2 = 0.91$) for density-independent and product of wood density, square of diameter and height ($R^2 = 0.94$) for density-dependent model showed the strongest fit statistics and smaller variations of the residuals. The developed models were well validated as the correlation coefficients between

observed and predicted values ranged from high (0.87) to very high (0.97) and the difference between observed and predicted values was non-significant. As the predicted biomass by the models of this study differed significantly with the predicted biomass by the previously developed models of *Shorea robusta*, site and size specific models are required for accurate prediction of biomass of *Shorea robusta*. Future research is recommended from a wider geographical area including the variables that describes site quality, stand density, growth stage, climate and species distribution to make the model more applicable in wider areas.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Author contribution

The first author designed a research concept, carried out data collection, developed models and drafted the manuscript. The second author played a coordinating role in model development, manuscript writing and edited the manuscript thoroughly.

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