



## Predictive biomass equations of chir pine silvipasture ecosystem of Himalayas, India

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### Abstract

In the present study, the above-ground herbaceous biomass was examined, and species-specific and multispecies power-law allometric equations for six dominant grass species of chir pine silvipasture ecosystem were developed, considering basal area and number of tillers as a predictor. The mean above ground herbaceous biomass and carbon content were estimated to be  $3.02 \pm 0.16 \text{ Mg ha}^{-1}$  and  $1.36 \pm 0.7 \text{ Mg C ha}^{-1}$ , respectively. All allometric relationships fitted to similar power-law models, with the basal area as the most influential predictor for the majority of grass species, however, the number of tillers proved to be a good predictor for above ground biomass of *Panicum maximum*. Although the fit improved when the number of tillers and basal area were combined in the model. Species-specific equations gave much better fits than multispecies allometric equations. A validation test indicated that these models made a precise prediction of grass biomass of the region.

**Keywords:** Allometric equation, Biomass, Carbon stock, Grassland, Mid-hill region, Silviculture

### Introduction

Vegetation biomass is a measure of ecosystem productivity, sustainability and health (Navar *et al.*, 2004; Ghosh and Mahanta, 2014; Galidaki *et al.*, 2017). One of the crucial variables to counteract the looming danger of climate change is vegetation biomass. The accumulated biomass is a measure of stocks and fluxes of carbon within the earth's terrestrial ecosystem (Schimel *et al.*, 2000; Houghton, 2007) and can be used for the adoption of a carbon compensation mechanism. The biomass is managed not only for environmental amelioration but also to improve the socio-economic condition of people (Yadav *et al.*, 2018). Further, a study in this aspect identifies the threats to the ecosystem from advancing anthropogenic

and climatic changes, allowing management policies to be developed (Oliveras *et al.*, 2013).

The destructive method of vegetation biomass estimation is expensive and time-consuming (He *et al.*, 2018). Besides, the use of destructive sampling is riskier particularly in the hilly terrains as well as in degraded areas. Here the disturbances to the ground vegetation cause many adverse effects such as soil erosion, loss of gene pool etc. Estimation of biomass with remote sensing technology requires location-specific field-based measurement for calibration and validation (Chave *et al.*, 2019). A biomass estimation method based on allometric equations requires one-time initial extensive destructive sampling of biomass and later can be used for estimating biomass and productivity in a non-destructive way with more consistency (Sala and Austin, 2000). Allometric equations use the correlation between biomass and plant dimensions like height, basal diameter (area), canopy volume, canopy diameter (Brown, 1997; Chave *et al.*, 2005; Nath *et al.*, 2019). This method is less costly, time-efficient, higher precision due to greater sampling efficiency (Reese *et al.*, 1980). Many other researchers have already reported that grasses-basal diameter (area), number of tillers, height may be the best predictor for the current year biomass estimation of grasses (Guevara *et al.*, 2002; Nafus *et al.*, 2009; Oliveras *et al.*, 2013). Currently, there are many region-specific allometric equations developed for woody perennials like trees (FSI, 1996; Brown, 1997; Chave *et al.*, 2005; FSI, 2009; FSI, 2013; Nath *et al.*, 2019; Rathore *et al.*, 2021), shrubs (Navar *et al.*, 2004; Mandal and Joshi, 2015) and bamboos (Kaushal *et al.*, 2016; Huy *et al.*, 2019; Xayalath *et al.*, 2019). However, very few predictive equations have been developed for grasses. The species-specific equation for grass biomass estimation has been developed for grasslands of south-eastern Peruvian Andes (Oliveras *et al.*, 2013), Mendoza,

### Predictive equations for grass biomass

Argentina (Guevara *et al.*, 2002), semi-desert rangeland of Arizona (Nafus *et al.*, 2009). However, this finding is not universal. The general allometric equation developed for multiple species, locations as well as land uses can reduce the investment needed to develop many species-specific equations and may have wider applicability than species-specific models (Lambert *et al.*, 2005). However, these general equations have been found moderately successful for trees and shrubs (Singh 1986; Buech and Rugg, 1989; Jenkins *et al.*, 2003; Lambert *et al.*, 2005). The multispecies model utility is limited when the model is applied to an area with different species combinations. Interspecific variation in the biomass-size relationship due to repeated defoliation may make it difficult to generalize across sites with different grazing histories (Peterson, 1962; Trlica and Orodho, 1989; Kotanen and Bergelson, 2000). Under this condition, basal area and number of tillers could be more reliable independent variable that has a very good correlation with grass biomass. The assessment of biomass of herbaceous vegetation through a predictive model is still lacking for chir pine silvipasture ecosystems of the Himalayas. Therefore, the present study was formulated with the following objectives: (i) to develop predictive biomass equations for the common grass species of the mid-hill region of western Himalaya using one or more dimensions and (ii) to check the validity of these equations in predicting biomass.

#### Materials and Methods

**Study area:** The study was conducted in chir pine silvipasture (SPCP) ecosystem located at the mid-hill region of Himachal Pradesh in Solan district, India. This silvipasture is one of the most important ecosystems of this region and is well distributed throughout an approximate altitude range between 1000-1700 m above mean sea level (m.s.l.). The ground vegetation of this silvipasture is the main source of fodder for livestock and the overstorey tree species *i.e.*, *Pinus roxburghii* is tapped for resin production. This ecosystem has been developed over ages in the Himalayas as a result of interaction among climate, soil as well as anthropogenic activities. Cut and carry systems of fodder management are commonly practised in this silvipasture. The local inhabitants are

constantly involved in creating optimal conditions for herbage growth by regularly burning the litter in this silvipasture before the commencement of rains. SPCP is experiencing increased degradation from fire, low management, changing climate etc. The common grasses found in SPCP are *Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Panicum maximum* and *Themeda anathera*. The climate of the area represents transitional between sub-tropical and sub-temperate. The area receives an average annual rainfall of 1000-1200 mm and experiences relative humidity of 50% with a range of 35-80%. The soil comprises carbonaceous shales, calcareous shales, dolomite limestone with bands of intermittent shales in the area (Gupta *et al.*, 2009).

**Data collection:** An extensive survey of the study region was carefully conducted to select randomly twelve sites of chir pine silvipasture ecosystem present in the region (Table 1). A total of 84 quadrats of 0.25 m<sup>2</sup> size were laid out in SPCP during the growing season of the year 2017 for herbage sampling. The quadrat size was decided as per the species-area curve (Gupta *et al.*, 2015). In each selected sites of SPCP, seven quadrats of 0.25 m<sup>2</sup> were delineated. The herbs falling under each quadrat were uprooted at the peak growing period. The numbers of herbage species in each quadrat, as well as the tillers of each species, were counted and their basal girth was determined at ground level. Basal area was derived from the basal girth of each plant. The above-ground biomass of herbs species was obtained by separating the above-ground part of the individual grass species and dried in an oven at 70°C to constant weight and weighed to the nearest 0.1 g. Aboveground carbon content in plants was determined by multiplying biomass of herbs with a conversion factor of 0.45 (Woomer, 1999; Magnussen and Reed, 2004).

**Predictive models:** Species-specific predictive regression models were developed for six dominant grasses (*Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Panicum maximum* and *Themeda*

**Table 1.** Latitude, longitude and elevation of the study sites

Sl. No.	Study site	Lat-long (degree, minutes, seconds)	Elevation (meter asl)
1.	Padhan	30°51'17.34"N and 77°09'50.28"E	1159
2.	Radiana	30°59'7.38"N and 76°59'00.12"E	1200
3.	Ambar	30°51'35.46"N and 77°11'9.06"E	1247
4.	Jabli Kiar	30°52'7.98"N and 77°07'57.24"E	1291
5.	Dharan	30°53'25.32"N and 77°11'07.68"E	1384

*anathera*) of chir pine silvipasture ecosystem in the mid-hill zone of Himalaya, which constituted 72.81% of total herbaceous biomass and 82.25% of total grass biomass. It was evident that grass biomass growth form was allometric type, suitable for developing predictive equation (Oliveras et al., 2013). In addition, common equations for the six species were also developed using data integration of the six species. Here six grass species were considered for modelling purpose, since they constituted 78.49% of the total herbaceous vegetation density and 86.22% of the grass density in chir pine silvipasture ecosystem.

From the extensive reviewing of research articles (Oliveras et al., 2013; Kaushal et al., 2016; Rathore et al., 2021), several popular regression models were considered for predictive modelling of above-ground biomass and after initial fitting; it was observed that many non-linear regression models were not fitted. Therefore, overall 14 models of which 3 linear, 4 curvy-linear (e.g., quadratic and cubic) and 7 non-linear type models were selected for performance evaluation to find out the best-fitted model (Table 2).

The parameters of the linear regression and curvy-linear models were estimated using the ordinary least square estimation method whereas non-linear regression

equations were determined by the non-linear (weighted) least-squares method using the Gauss-Newton algorithm and analysed it by applying 'nls' function of R software. One of the most popular methods to fit allometric or power-law equation was taking logarithmic transformation of both sides of the equation, that converted it to linear relationships. However, it was reported that the power-law equation and log-transformed models had different stochastic characteristics (Gingerich, 2000; Kerkhoff and Enquist, 2009; Xiao et al., 2011). Oliveras et al. (2013) estimated above-ground biomass as a response variable in tropical alpine tussock using an allometric equation, and basal area, crown area and maximum height were used as regressor variables. Here basal area (m<sup>2</sup>) and number of tillers (discrete count) were used for the prediction of above-ground biomass (g).

**Statistical analysis:** First, each species-specific data sets with sample size ranged from 23 to 66, were randomly split into two subsets, training data (80%) used for fitting the models (or model development) and testing data (20%) used for validation of the fitted models. Pearson's correlation coefficient analysis (at p-value 0.05) was done to find out degree of relationships between different parameters for each of the six species and 6 species combined data. In modelling, among the predictive models,

**Table 2.** Predictive regression models (linear and non-linear)\* tested for above-ground biomass estimation (AGB)

Model code	Model	Equation
M1	Linear	$AGB = a + b(NT) + \varepsilon$
M2	Quadratic	$AGB = a + b(NT) + c(NT)^2 + \varepsilon$
M3	Cubic	$AGB = a + b(NT) + c(NT)^2 + d(NT)^3 + \varepsilon$
M4	Allometric	$AGB = a(NT)^b + \varepsilon$
M5	Gompertz	$AGB = a \exp(-b \exp(cNT)) + \varepsilon$
M6	Logistic	$AGB = a / [1 + b \exp(-cNT)] + \varepsilon$
M7	Linear	$AGB = a + b(BA) + \varepsilon$
M8	Quadratic	$AGB = a + b(BA) + c(BA)^2 + \varepsilon$
M9	Cubic	$AGB = a + b(BA) + c(BA)^2 + d(BA)^3 + \varepsilon$
M10	Allometric	$AGB = a(BA)^b + \varepsilon$
M11	Gompertz	$AGB = a \exp(-b \exp(cBA)) + \varepsilon$
M12	Logistic	$AGB = a / [1 + b \exp(-cBA)] + \varepsilon$
M13	Linear	$AGB = a + b(NT) + c(BA) + \varepsilon$
M14	Allometric	$AGB = a(NT)^b (BA)^c + \varepsilon$

### Predictive equations for grass biomass

the best-fitted model was identified by applying three statistical criteria, given as: adjusted coefficient of determination ( $R^2_{adjusted}$ ), Akaike Information Criteria (AIC) given by Akaike (1974), and Bayesian Information Criteria (BIC) defined by Ernst *et al.* (2012). Further, to find out the fitted model with the highest prediction accuracy, validation of the fitted model was done using three criteria:

First, mean absolute percentage error (MAPE) given as

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{A_i - P_i}{A_i} \right| \times 100 \quad (1)$$

Where, A and P denoted Actual value and Predicted value, respectively.

Second, minimum maximum accuracy (MMA) with the formula,

$$MMA = \frac{n^{-1} \sum_{i=1}^n \text{minimum}(A_i, P_i)}{n^{-1} \sum_{i=1}^n \text{maximum}(A_i, P_i)} \quad (2)$$

Third, residual absolute mean (RAM) with the formula,

$$RAM = n^{-1} \sum_{i=1}^n |A_i - P_i| \quad (3)$$

Where, A and P already explained as actual value and predicted value, respectively.

For model validation paired t-test between the observed value and model predicted values were also done assuming the null hypothesis that there was no significant difference between observed and predicted values. Further, residuals normality and randomness were tested using SWNT and Bartels Ratio Test for randomness (BRTR), respectively. All the statistical analysis was conducted using nlme package of R Studio software (R version 4.0.2).

### Results and Discussion

**Above-ground biomass and carbon stock:** The above-ground herbaceous vegetation (grasses+sedges+forbs+legumes) biomass and carbon stock in chir pine silvipasture ecosystem were estimated to the tune of  $3.02 \pm 0.16$  Mg ha<sup>-1</sup> and  $1.36 \pm 0.07$  Mg C ha<sup>-1</sup>, respectively. The biomass of herbaceous vegetation in a similar range was reported by Gupta *et al.* (2015), Singh *et al.* (2015) and Yadav *et al.* (2019) from silvipastures of the Himalayan region and Yang *et al.* (2018) from grassland of the Loess Plateau, China. Whereas, the biomass of the present study was at a higher-end than the biomass of alpine grasslands of Tibet, China and Manag district, Nepal (Bhandari and Zhang, 2019) and it was in the lower end than the value reported in Chiapas, Mexico by Soto-Pinto *et al.* (2010).

Regional variability mainly could be due to differences in climatic, edaphic as well as biotic conditions which might have caused variation in the overall system's production capacity (Bhutia *et al.*, 2021). Furthermore, there was a significant role of system management in biomass built up and also differences in sampling methods including sampling size and time of sampling might have led to variations in the data. A total of 61 herbaceous species were reported under 4 plant categories (22 grasses; 5 sedges; 30 forbs; 4 herbaceous legumes). Out of all categories, grasses were the major contributor of above ground herbaceous biomass of chir pine silvipasture ecosystem constituting around 88.32% of total herbaceous aboveground biomass. *Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Panicum maximum* and *Themeda anathera* were the major contributing grass species accounting for 7.44%, 7.22%, 26.64%, 22.01%, 5.80%, and 13.13% of the total grass above-ground biomass, respectively. Their total contribution to the total above ground herbaceous biomass and grass biomass were 72.81% and 82.25%, respectively. The number of herbaceous species reported in the present study were in the range reported earlier (Gupta and Sharma, 2015; Gupta *et al.*, 2015; Husain *et al.*, 2019).

**Vegetation density and basal area:** The average density and basal area of herbaceous vegetation in SPCP ecosystem were 890 tillers/m<sup>2</sup> and 48.93 cm<sup>2</sup>/m<sup>2</sup>, respectively. The majority of herbaceous vegetation density and basal area were contributed by 6 major grass species viz., *Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Panicum maximum* and *Themeda anathera*.

**Correlation coefficient analysis:** The linear relationship between three parameters for six grasses (individually and combined) viz., above-ground biomass (AGB), number of tillers, basal area was done using Pearson's correlation coefficient analysis. The lowest value (0.72) was observed between basal area and AGB for a combined six grasses and the highest value (0.98) between basal area and AGB for *Apluda mutica*.

**Model fitting:** Fourteen predictive models were fitted on the training data set. First, species-specific fitting for the six species (*A. mutica*, *A. nepalensis*, *C. fulvus*, *H. contortus*, *P. maximum* and *T. anathera*) were done independently. Thereafter, model fitting of combined six species data was done to develop a combined species model.

For the grass species *Apluda mutica*, it was revealed that the basal area (BA) was a good fit, whereas the number of tillers (NT) did not fit well, but NT along with the BA, slightly improved the model fitting. Therefore, allometric model M10 and M14 were found to be the best fit model, out of 14 models (M10: adj-R<sup>2</sup>= 0.965, AIC= 159.33 and BIC=163.22; M14: adj-R<sup>2</sup>= 0.974, AIC= 152.59 and BIC=157.77) (Table 3). Similarly for other grass species like *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Themeda anathera*, BA was observed to be a good fit over NT, but the addition of NT along with BA slightly improved the model fitting for all the species. Thus the allometric model M10 and M14 were also best fitted for all four species, *Arundinella nepalensis* (M10: adj-R<sup>2</sup>= 0.750, AIC= 131.50 and BIC=134.33; M14: adj-R<sup>2</sup>= 0.785, AIC= 129.13 and BIC=130.91) *Chrysopogon fulvus* (M10: adj-R<sup>2</sup>= 0.800, AIC= 405.60 and BIC= 411.22; M14: adj-R<sup>2</sup>=0.855, AIC= 365.40 and BIC=371.88), *Heteropogon contortus*. (M10: adj-R<sup>2</sup>=0.66, AIC= 429.31 and BIC=435.28; M14: adj-R<sup>2</sup>= 0.69, AIC=406.96 and BIC=401.92), *Themeda anathera* (M10: adj-R<sup>2</sup>= 0.792, AIC= 221.18 and BIC=226.02; M14: R<sup>2</sup>=0.809, AIC=206.30 and BIC=212.75) (Table 4-6, 8). However, NT was found to be a good fit over BA for *Panicum maximum*, but the inclusion of BA along with NT improved the overall model fitting. The allometric model M4 and M14 found as best fit model (M4: adj-R<sup>2</sup>= 0.838, AIC= 128.21, BIC=131.34; M14: adj-R<sup>2</sup>= 0.853, AIC= 121.76, BIC= 125.93 (Table 7). In multi-species model fitting of the six grass species confirmed that model M14 as the best model with the highest adj-R<sup>2</sup> (0.757), lowest AIC (1211.69) and BIC (1224.88) value, similar to species-

specific results (Table 9). Comparing the results of the multi-species analysis with species-specific models, the multi-species model had a lower adj-R<sup>2</sup> value and higher AIC and BIC values. It was because within multispecies data, species-specific AGB allometric growth varied themselves with model parameters ranged from 0.28 to 33.20 for a, -0.32 to 1.243 for b, and -0.0599 to 1.10 for c.

In the present study, it was observed that morphological characters such as basal area and number of tillers were reliable variables for above-ground biomass estimation of dominant grass species of chir pine silvipasture ecosystem, using allometric equations. Basal area was found to be the most significant predictor for species like *Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus* and *Themeda anathera*, however, for *Panicum maximum*, the number of tillers was found to be a good fit. Several studies conducted in different types of grasslands in other parts of the world showed that basal area (Nafus et al., 2009; Andariese and Covington, 1986; Johnson et al., 1998) and number of tillers (Guevara et al., 2002) were the major explanatory variables for tussock and rhizomatous grasses, respectively. It was also found that the use of two variables in combination like basal area and number of tillers improved the model fitting for all the species investigated and as well as for combined one. These findings were inconsistent with previous work in grasses, where they reported little improvement in predictive strength with the addition of parameters like plant height to species-specific or multispecies models that already contained diameter of tussock grasses (Andariese and Covington, 1986;

**Table 3.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Apluda mutica*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	-6.59	0.81			0.422	235.17	239.06
M2	-0.17	0.28	0.01		0.409	236.60	241.78
M3	2.85	-0.11	0.02	-0.0001	0.384	238.52	245.00
M4	0.09	1.52			0.434	234.60	238.49
M5	120.87	4.51	0.02		0.412	236.46	241.65
M6	71.12	34.79	0.07		0.418	236.21	241.39
M7	0.45	10.80			0.865	169.23	173.12
M8	1.67	9.12	0.21		0.910	162.65	169.84
M9	-0.09	13.14	-1.15	0.1027	0.920	159.14	168.62
M10	10.62	1.01			0.965	159.33	163.22
M11	150.67	3.40	0.24		0.952	169.06	174.24
M12	118.99	16.86	0.52		0.934	177.49	182.67
M13	2.83	-0.12	11.66		0.869	166.62	171.80
M14	33.20	-0.32	1.10		0.974	152.59	157.77

### Predictive equations for grass biomass

**Table 4.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Arundinella nepalensis*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	4.74	0.28			0.739	132.36	135.19
M2	3.10	0.36	-0.0004		0.730	133.73	137.51
M3	0.46	0.60	-0.0046	0.00002	0.726	134.72	139.44
M4	0.53	0.10			0.588	141.02	143.85
M5	62.58	2.48	0.0150		0.714	134.81	138.59
M6	56.59	7.53	0.0262		0.695	136.04	139.82
M7	2.58	6.37			0.595	140.68	143.51
M8	4.02	4.66	0.2956		0.571	142.52	146.30
M9	6.09	0.34	2.2151	-0.22103	0.546	144.33	149.05
M10	8.45	0.87			0.750	131.50	134.33
M11	75.25	2.79	0.2595		0.574	142.40	146.18
M12	49.68	9.00	0.6241		0.578	142.22	146.00
M13	2.86	0.21	2.1982		0.754	131.96	135.74
M14	1.78	0.55	0.2960		0.785	129.13	130.91

**Table 5.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Chrysopogon fulvus*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	-8.05	0.43			0.796	406.50	412.11
M2	-4.136	0.333	0.0004		0.794	407.98	415.46
M3	9.217	-0.174	0.0049	-0.00001	0.801	407.28	416.64
M4	0.089	1.279			0.655	431.71	437.32
M5	141.5	4.098	0.0099		0.804	405.65	413.13
M6	110.4	25.21	0.0217		0.809	404.38	411.87
M7	0.69	5.478			0.649	432.54	438.15
M8	-9.465	9.2266	-0.195		0.689	427.65	435.13
M9	7.775	-1.88	1.15	-0.039	0.767	414.71	424.06
M10	7.135	0.90			0.800	405.60	411.22
M11	107.33	4.345	0.216		0.720	422.60	430.09
M12	102.77	20.949	0.357		0.728	421.20	428.68
M13	-8.11	0.369	1.049		0.798	406.96	414.45
M14	0.151	1.087	0.20		0.855	365.40	371.88

Assaeed, 1997; Johnson *et al.*, 1998; Guevara *et al.*, 2002; Nafus *et al.*, 2009). However, research in tropical alpine tussock grasslands conducted by Oliveras *et al.* (2013) indicated that the addition of variables like plant height improved the model efficiency for some grass species investigated. The species-specific allometric equations for all grass species investigated showed better fits than the multispecies model. Therefore, the species-specific model developed based on basal area and number of tillers would be most appropriate and should be used for precise estimation of above-ground biomass and carbon stock estimation of grass species in chir pine silvipasture ecosystem. However, the multispecies model could be used in reconnaissance surveys for a rough estimation of

the above-ground biomass and carbon stock measurement of grasses as it eliminates the need for species identification and destructive sampling. These allometric models developed may be applicable in most grassland or silvipasture ecosystems of the Himalayas with similar species composition. However, studies on its validation for other regions would be very useful to test its wider applicability, especially in areas with different environmental factors or different species composition.

**Model validation:** Prediction accuracy of 14 fitted models was measured using three standard cross-validation methods [MAPE (Eq. 1), MMA (Eq. 2) and RAM (Eq. 3)]. The MAPE and RAM indicated the prediction error, hence

**Table 6.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Heteropogon contortus*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	0.867	0.315			0.56	459.53	465.49
M2	-1.05	0.376	-0.0003		0.55	460.99	468.95
M3	1.08	0.258	0.0009	-0.000003	0.55	462.57	472.52
M4	0.4525	0.9315			0.44	479.05	485.01
M5	94.34	3.187	0.011		0.55	461.26	469.22
M6	85.957	12.995	0.019		0.54	462.18	470.13
M7	11.28	2.449			0.16	494.19	500.16
M8	2.17	7.81	-0.357		0.29	485.98	493.94
M9	2.50	7.48	-0.306	-0.002	0.28	487.97	497.92
M10	13.844	0.435			0.66	429.31	435.28
M11	41.49	2.30	0.44		0.25	488.74	496.69
M12	41.476	6.31	0.626		0.25	488.82	496.78
M13	0.0334	0.297	0.476		0.56	460.82	468.78
M14	0.159	1.243	-0.291		0.69	406.96	401.92

**Table 7.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Panicum maximum*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	1.31	0.20			0.836	130.53	133.67
M2	0.44	0.24	-0.0003		0.833	131.76	135.94
M3	0.70	0.22	0.0001	-0.0000013	0.823	133.70	138.93
M4	0.40	0.86			0.838	128.21	131.34
M5	40.14	3.05	0.0170		0.832	131.80	135.97
M6	36.16	12.22	0.0310		0.823	132.90	137.07
M7	5.10	3.19			0.566	150.94	154.07
M8	3.37	5.37	-0.2060		0.587	150.70	154.88
M9	1.98	8.81	-1.1200	0.053	0.575	152.04	157.26
M10	9.93	0.55			0.619	148.24	151.37
M11	37.62	2.19	0.3510		0.580	151.08	155.26
M12	35.40	6.39	0.5820		0.568	151.64	155.82
M13	1.20	0.21	-0.3590		0.828	132.26	136.44
M14	0.28	0.96	-0.0599		0.853	121.76	125.93

a value near to zero indicated high accuracy whereas MMA directly indicated prediction accuracy, therefore a value near to 1 (decimal form) indicated perfect prediction. In species-specific and multi-species model validation, lowest MAPE and RAM values and highest MMA value were observed for allometric model M14 in *Apluda mutica* (MAPE=0.336, RAM=0.862 and MMA=0.895), *Arundinella nepalensis* (MAPE=0.284, RAM=1.584 and MMA=0.825), *Chrysopogon fulvus* (MAPE=0.484, RAM=1.00 and MMA=0.773), *Heteropogon contortus* (MAPE=0.537, RAM=0.725 and MMA=1.30), *Panicum maximum* (MAPE=0.243, RAM=1.954 and MMA=0.837), *Themeda anathera* (MAPE=0.40, RAM=0.449 and MMA=0.77) and

Combine 6 species (MAPE=0.35, RAM=1.281 and MMA=0.747).

To know that predicted values were similar to the observed values, paired t-test (null hypothesis: observed and predicted values same) at p=0.05 was done and results showed that the Model M14 was non-significant for both species-specific and multi-species cases. Further, normality by SWNT (null hypothesis: residuals were normally distributed) and randomness of the residuals by BRTR (null hypothesis: residuals are independent) were also tested for statistical validation. The test results were found as non-significant, which confirmed the normality

### Predictive equations for grass biomass

**Table 8.** Predictive models for above-ground biomass (AGB) estimation for the grass species *Themeda anathera*

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	1.608	0.202			0.726	233.36	238.19
M2	0.816	0.243	-0.0003		0.721	234.92	241.36
M3	-2.46	0.517	-0.005	0.00002	0.743	232.79	240.85
M4	0.504	0.82			0.764	224.38	228.21
M5	35.51	2.649	0.0178		0.702	237.39	243.83
M6	29.04	8.346	0.035		0.682	239.77	246.21
M7	3.433	3.45			0.713	235.15	239.98
M8	1.816	5.154	-0.207		0.728	234.05	240.49
M9	0.94	7.07	-0.828	0.046	0.726	235.11	243.17
M10	7.538	0.655			0.792	221.18	226.02
M11	33.12	2.399	0.379		0.717	235.55	242.00
M12	30.81	7.177	0.635		0.704	237.20	243.64
M13	1.845	0.114	1.722		0.764	228.83	235.28
M14	1.822	0.411	0.3877		0.809	206.30	212.75

**Table 9.** Predictive model fitting for above-ground biomass (AGB) prediction of six grass species combined (*Apluda mutica*, *Arundinella nepalensis*, *Chrysopogon fulvus*, *Heteropogon contortus*, *Panicum maximum* and *Themeda anathera*)

Sl. No.	Fitted model coefficient				Adj-R <sup>2</sup>	AIC	BIC
	a	b	c	d			
M1	-0.409	0.324			0.635	1611.81	1621.71
M2	3.015	0.197	0.00062		0.645	1606.91	1620.11
M3	0.221	0.374	-0.001	6.34×10 <sup>-6</sup>	0.650	1605.251	1621.74
M4	0.197	1.10			0.563	1588.97	1598.87
M5	253.81	3.791	0.0053		0.639	1610.28	1623.47
M6	136.33	18.67	0.015		0.634	1613.21	1626.41
M7	6.633	3.679			0.428	1701.56	1711.45
M8	2.55	6.29	-0.17		0.470	1686.47	1699.67
M9	2.69	6.148	-0.149	-0.0007	0.470	1688.46	1704.95
M10	10.39	0.63			0.669	1509.99	1519.88
M11	59.49	2.52	0.257		0.470	1687.55	1700.75
M12	55.87	8.25	0.437		0.467	1688.58	1701.78
M13	-0.518	0.279	0.827		0.643	1608.24	1621.43
M14	0.245	1.037	0.046		0.757	1211.69	1224.88

and independence of the residuals. Overall the performances of the M14 models were consistent with validation set data for all the validation criteria.

#### Conclusion

The study showed that basal area and number of tillers provided a reliable basis for above-ground biomass and carbon stock estimation for common grasses of chir pine silvipasture ecosystem, using the allometric predictive regression model. The accuracy of the allometric equation by basal area and number of tillers solely, good predictor, but putting them both in the allometric equation always improved the goodness of fit of the model. All the species-

specific models gave better goodness of fit than a multi-species model except for the grass species *Heteropogon contortus*. These equations developed would be useful to measure the grass productivity in the grassland or silvipasture ecosystem and for the establishment of reference levels prior to the adoption of carbon compensation mechanism, grassland management policies as well as for determining land-use change impact in the Himalayan ecosystem.

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### Predictive equations for grass biomass

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**Bhutia et al.**

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