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Estimating biomass and carbon mitigation of temperate coniferous forests using spectral modeling and field inventory data

Akhlaq Amin Wani [a,b,*], Pawan Kumar Joshi [c], Ombir Singh [a]

[a] Silviculture Division, Forest Research Institute (FRI) Dehradun, Uttarakhand-248006, India
[b] Faculty of Forestry, Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Campus (Wadura) J&K-193201, India
[c] Department of Natural Resources, TERI University New Delhi, 110070, India

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ABSTRACT

Realizing the importance of forest carbon monitoring and reporting in climate change, the present study was conducted to derive spectrally modeled aboveground biomass and mitigation using Landsat data in combination with sampled field inventory data in the coniferous forests of Western Himalaya. After conducting preliminary survey in 2009, 90 quadrats (45 each for calibration and validation) of 0.1 ha were laid in six forest types for recording field inventory data viz. diameter at breast height, height, slope and aspect. Biomass carbon (Mg ha^{-1}) was worked out for different forest types and crown density classes (open with 10–40% crown density and closed with >40% crown density) using recommended volume equations, ratios and factors. Biomass carbon map (aboveground + belowground) was generated for the entire region using geospatial techniques. Normalized difference vegetation index (NDVI) was generated and spectral values were extracted to establish relation ($R^2 = 0.72$, $p < 0.01$) with the field inventory data. The model developed was validated ($R^2 = 0.73$, $p < 0.01$) with 45 sample observations not used earlier for predicting and generating biomass carbon map (2009) for the entire region. The data from field based inventory indicates highest total biomass carbon (171.40, $\sigma \pm$ 23.19) Mg ha^{-1} for Fir–Spruce (closed) which has relatively more mature girth classes and low tree density. This value was found to be significantly higher than other forest types. Lowest biomass carbon was observed for Blue Pine (open) (37.15, $\sigma \pm$ 11.82) Mg ha^{-1}. The NDVI values for the entire region ranged from 0 to 0.62 and consequently the spectrally derived aboveground biomass carbon varied from 0 to 600 Mg ha^{-1}. The study demonstrates the application of mapping, spectral responses and sampled field inventory for type wise assessment of carbon mitigation in temperate coniferous forests of Himalayas.

1. Introduction

Forest ecosystems recognized as the critical components in the global carbon are estimated to contain 80% of the aboveground (AG) and 40% of the belowground (BG) terrestrial carbon stocks (Brown and Lugo, 1984; Dixon et al., 1994). Recent estimates have shown the current carbon stock in the world's forests to be 861 ± 66 Pg with 383 ± 30 (44%) in soil (to 1 m depth), 363 ± 28 Pg (42%) in live biomass (AG and BG), 73 ± 6 Pg (8%) in deadwood, and 43 ± 3 Pg (5%) in litter (Pan et al., 2011). However other estimates indicate to contain 450 to 650 Pg in vegetation biomass (IPCC, 2013; Prentice et al., 2001) and 1500 to 2400 Pg in dead organic matter and soils (Batjes, 1996; IPCC, 2013). Forest loss accounts for a significant share of global greenhouse gas emissions estimated between 12% (Van der Werf et al., 2009) and 17% (IPCC, 2007). The increasing concern for climate change at national and international level has led to increased focus on sustainable carbon management in forestry (FAO, 2010). Carbon estimates in forests are significantly important for locations which have data gaps like Himalayan region of Kashmir and the north western part of Indian Himalayas which pose great challenges to collect information on carbon forestry. Moreover a long gestation period is involved in developing and implementing adaptation strategies in forestry sector (Ravindranath and Sathaye, 2002) which makes it difficult to efficiently monitor the forests.

In the present scenario carbon management is viewed as an important activity in the context of greenhouse and climatic changes at national and international level (Ravindranath and Ostwald, 2008). Hence, it becomes extremely important to produce regional estimates regarding the dynamics in carbon to assess the role of forestry in climate change (Fang et al., 2006). The role of forests in mitigating climate change is actively being considered under the agenda of reducing emissions from deforestation in developing countries REDD+ (UNFCCC, 2008). Geospatially valid carbon monitoring and accounting would lead to increase in international agreements on carbon emissions in context to REDD+ (Angelson, 2008; Asner et al., 2012; De Sy et al.,

* Corresponding author at: Faculty of Forestry, Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Campus (Wadura) J&K-193201, India. Tel./fax: +91 1952 262212, +91 9797011395 (cell).
E-mail address: akhlaqwani@yahoo.co.in (A.A. Wani).

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2012). Geospatial mapping of forest resources based on field plot inventory data has enabled to extrapolate the sample data over larger scales (Asner, 2009; Asner et al., 2013; Baccini et al., 2013; Goetz et al., 2009; Saatchi et al., 2011). Although very recently airborne LIDAR borne sample data integrated with satellite data and in-situ observations generate more efficient forest carbon maps (Gautam et al., 2010; Kandel, 2013; Kandel et al., 2014) however, the technique is yet to evolve in this Kashmir Himalayan region due to political hindrances and high costs. Aboveground and belowground biomass form the predominant carbon pools followed by soil, litter and deadwood (IPCC, 2003, 2006). The results regarding carbon densities however, vary owing to heterogeneity across forest types (Houghton et al., 2009) and adoption of different methodologies (Kishwan et al., 2009). This paper discusses biomass carbon values for different forest types and density classes in the coniferous forests of Western Himalayan region. Our results generate data on forest biomass carbon (AG and BG) to establish relation between biomass field inventory data and spectral values of vegetation index estimated from satellite data.

2. Methods

2.1. Study area

Geographically the area under investigation lies approximately between 33° 21′ 57.6″ to 34° 15′ 25.2″ north latitude and 74° 52′ 58.8″ to 75° 32′ 20.4″ east longitude (Fig. 1). The area occupies southern portion of Kashmir Himalayas. It has an annual precipitation of 660–1400 mm with an average temperature of around 13 °C which also goes subzero in winter months. The main forest types include Lower western Himalayan temperate forest, West Himalayan dry temperate deciduous forest, West Himalayan subalpine Fir forest, deciduous alpine scrub and alpine pastures (Champion and Seth, 1968). The forests in the region are predominantly coniferous with some mixed composition at few places (Champion and Seth, 1968; Joshi et al., 2001). The conifers include Blue Pine (*Pinus wallichiana*), Himalayan Cedar (*Cedrus deodara*), Fir (*Abies pindrow*) and Spruce (*Picea smithiana*). Additionally associations of Himalayan Yew (*Taxus baccata*) and Juniper (*Juniperus recurva*) can also be found. The distribution pattern of conifers is guided by the elevation, climate, aspect, slope, geology and soil.

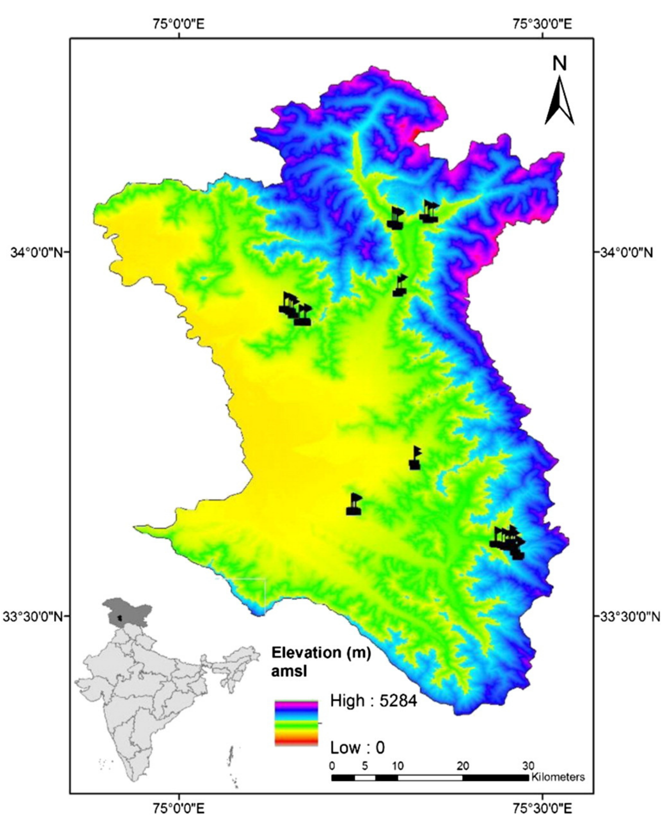

Fig. 1. Study area showing location of 0.1 ha sample quadrats (for interpretation of the references to color in this figure legend, the reader is referred to the web version of the article).

2.2. Pilot survey

We carried out a reconnaissance survey to collect preliminary information about the study area for developing a scheme of classification. Stratified random sampling design was adopted to choose the specific sampling sites on the basis of variability in vegetation. We divided the forest area into three primary strata on the basis of forest types: (i) Blue Pine, (ii) Fir–Spruce and (iii) Himalayan Cedar. Within these forest types simple random sampling was adopted for actual ground measurements (diameter at breast height and height of trees) for determination of variance. Sample size was obtained on the basis of variance in these ground measurements using the formula by Chako (1965):

$$n = \frac{t^2 \times CV^2}{(SE\%)^2}$$

where n = number of sample plots, CV = coefficient of variation, SE% = standard error percentage (10%) and t = statistical value at 95% significance level.

2.3. Field measurements

We carried out field measurements in the years 2010 and 2011 (June–October each year). Sample size (n) was worked out to be 45. All the square shaped sample quadrats (0.1 ha) were laid out in different forest types for tree measurements. Additional 45 quadrats of same shape and size were laid to generate data for validation of spectrally modeled biomass. Calibration and validation quadrats were selected randomly within each forest type. We measured diameter at breast height (DBH) and tree height (h) for all the trees having DBH >10 cm using Ravi multi-meter and tree caliper respectively. The position of quadrats was recorded using hand held global positioning system (GPS) unit. Additional information viz. slope, aspect, altitude, tree density etc. about the site was also recorded. We recorded canopy density for each sample plot with convex spherical crown densitometer by averaging the four readings inside each quadrat. The scheme of classification adopted for density classes was followed as per FSI (2005) with canopy density 10–40% for open forests and >40% for closed forests. The investigation sites were spread across five forest ranges (Table 1) with a significant variation in elevation and slope.

2.4. Volume and biomass and mitigation

Regression general equations (Table 2) were used as per volume equations recommended by FSI (1996).

We calculated volume of trees using DBH and height which was further converted into biomass (AG) using specific gravities of the respective species as per Rajput et al. (1996). We converted commercial bole into total aboveground biomass using biomass expansion factor (BEF) of 1.3 (FAO, 1997). Although more qualitative BEF based on forest age, forest density and forest site quality (Fang et al., 2002; Teobaldelli et al., 2009) or volume based (Guo et al., 2010) could have been used but such BEFs have not been worked out previously for these forest types in the region. We computed biomass (BG) using a factor of 0.26 as recommended by Cairns et al. (1997) which is very close to the ratio recommended for temperate coniferous forests (Mokany et al., 2006) with shoot biomass >50 Mg ha^{-1}. We further converted total biomass into carbon equivalent using a factor of 0.50 (Bhadwal and