CHAPTER - 4

Biomass and Carbon stock

4.1. Introduction

Forest ecosystems are the major biological scrubbers of atmospheric carbon dioxide in the terrestrial biomes. It removes nearly 3 billion tons of anthropogenic carbon every year (3 Pg C/year) through net growth, absorbing about 30% of carbon emissions from fossil fuel burning and net deforestation (Canadell et al., 2007 and Canadell and Raupach, 2008). The main carbon pools in tropical forest ecosystems are the living biomass of trees, understory vegetation, dead mass of
litter, woody debris and soil organic matter. The carbon stored in the aboveground living biomass of trees is typically the largest pool, more than double the amount of carbon in the atmosphere (Sabine et al., 2004 and FAO, 2006), and the most directly impacted by degradation and deforestation. Thus, estimating aboveground forest biomass carbon is the most critical step in global carbon cycle.

The most direct way to quantify the carbon stored in aboveground living forest biomass is by harvesting all trees in a known area, weigh the biomass and then multiply by a standard value of carbon concentration to produce an estimate of carbon stock (Kauppi et al., 1992 and Goodale et al., 2002). While this method is accurate for a particular location, it is prohibitively time-consuming, expensive and destructive. Tropical forests often contain 300 or more species, and the research has shown that species-specific allometric relationships are not needed to generate reliable estimates of forest carbon stocks. Instead, generalized allometric equations stratified by broad forest types are found to be highly effective for the tropics because GBH (Girth and Breast Height) alone explains more than 95% of the variation in aboveground tropical forest carbon stocks (Brown 2002). The left over problem with this approach is that it is measured at single sites, and is not readily scaled up.

The methods used for scaling up of forest biomass could be classified into two groups. Methods in the first group estimate biomass from remote sensing data (Foody et al., 2003; Lu, 2005; Broadbent et al., 2008; Anaya et al., 2009 and Fuchs et al., 2009), whereas methods in the second group employ interpolation of biomass estimates obtained in the field (Cheng et al., 2007; Sales et al., 2007 and
Lufafa et al., 2008). Though there are few studies in the second category, very few of them have compared the relative advantages of the various interpolation techniques. In this chapter, an effort has been made to estimate the biomass and carbon stock of major forest types in the study area and to identify the best interpolation technique for mapping the biomass and carbon stock.

4.2. Spatial Interpolation

Interpolation is a method to estimate the value of an unknown point from a number of known observations around that point (Myers, 1994). There are two main groups of interpolation techniques: deterministic and geostatistical. Deterministic interpolation techniques create surfaces from measured points, based on either the extent of similarity (Inverse Distance Weighted Average) or the degree of smoothing (Polynomial interpolation), while Geostatistical interpolation technique utilize the statistical properties of the measured points (Ordinary Kriging).

4.2.1. Inverse Distance Weighted (IDW) Interpolation

IDW interpolation explicitly implements the assumption that things that are close to one another are more alike than those that are farther apart. It assumes that each measured point has a local influence that diminishes with distance. It weights the points closer to the prediction location greater than those farther away. The formula for IDW is

\[ Z(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \]  

\[ 4.1 \]
where, $\hat{Z}(s_0)$ is the value to be predicted for location $s_0$, $N$ is the number of measured sample points surrounding the prediction location that will be used in the prediction, $\lambda_i$ are the weights assigned to each measured point that are going to be used, $Z(s_i)$ is the observed value at the location $s_i$. The formula to determine the weights is the following:

$$\lambda_i = d_{io}^{-p} / \sum_{i=1}^{N} d_{io}^{-p}$$

$$\sum_{i=1}^{N} \lambda_i = 1 \quad (4.2)$$

As the distance becomes larger, the weight is reduced by a factor of $p$. The quantity $d_{io}$ is the distance between the prediction location $s_0$ and each of the measured locations $s_i$.

**4.2.2. Polynomial interpolation**

Polynomial interpolation fits a smooth surface that is defined by a mathematical function (a polynomial) to the input sample points. For the first order trend, the model is

$$Z(x_i, y_i) = \beta_0 + \beta_1 x_i + \beta_2 y_i + \epsilon(x_i, y_i) \quad (4.3)$$

where, $Z(x_i, y_i)$ is the datum at location $(x_i, y_i)$, $\beta$ are parameters, and $\epsilon(x_i, y_i)$ is a random error.

**4.2.3. Ordinary Kriging (OK)**

Ordinary Kriging is a geostatistical technique which is similar to IDW in that it weights the surrounding measured values to derive a prediction for each location. However, the weights are based not only on the distance between the measured points and the prediction location but also on the overall spatial arrangement.
among the measured points. The unknown value $Z(s)$ at any location is typically decomposed into a mean (drift) component $\mu$ and a residual component $\epsilon(s)$ (equation 4.4).

$$Z(s) = \mu + \epsilon(s) \quad (4.4)$$

The predictor is formed as a weighted sum of the data (equation 4.5)

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \quad (4.5)$$

This equation is exactly similar to IDW interpolation. However, in IDW, the weight, $\lambda_i$, depends solely on the distance to the prediction location. In ordinary kriging, the weight, $\lambda_i$, depend on the semivariogram, the distance to the prediction location, and the spatial relationships among the measured values around the prediction location. The semi-variance is defined to be a function of the distances among observations.

### 5.3. Material and methods

Biomass was calculated using allometric equations developed for Western Ghats (Murali et al., 2005). Two allometric equations were used for this purpose. One was for evergreen forests (equation 4.7) and the other was for deciduous forests (equation 4.8). The Basal Area required for these equations was calculated from GBH using the equation (4.9). Carbon conversion coefficients are different, considering species, age, formation and community structure of vegetation types, from 0.45 to 0.55 (Kauppi et al., 1992; Goodale et al., 2002; Xia et al., 2005 and Ramachandran et al., 2007). Since such coefficients are not available for the study area, a carbon conversion coefficient of 0.5 is used in the present study. Carbon
storage of each forest type was estimated by multiplying forest carbon density per hectare into forest area.

\[
\text{Biomass Evergreen} = (-2.81 + 6.78 \cdot \text{Basal Area}) \quad (r^2 = 0.53) \quad (4.7)
\]

\[
\text{Biomass Deciduous} = (-73.55 + 10.73 \cdot \text{Basal Area}) \quad (r^2 = 0.82) \quad (4.8)
\]

\[
\text{Basal Area} = \frac{(GBH)^2}{4\pi} \quad (4.9)
\]

Spatial interpolation was conducted on the data to quantify the patterns of spatial variation in carbon stock. From the total sample points (206 sample points), a subset of 155 sample points (75%) were taken randomly for model generation (training datasets) and the remaining 51 sample points (25%) were used for model validation (testing datasets). Three interpolation techniques were applied. Inverse Distance Weighted interpolation was the first one implemented. The power value for IDW is optimised by considering the root mean square (RMS) error. At least ten neighbouring points were included in the prediction of unknown point. The second method was to fit a first order polynomial equation (local polynomial interpolation) to the sample points. The selection of first order was based on the least RMS error. At least ten neighbouring points were included as in the case of IDW.

Ordinary kriging was the third method implemented for interpolation of training datasets. The changes in semivariance with distance was analysed using different models such as circular, spherical, exponential and Gaussian, and found that the spherical model was the best choice since it has given the lowest RMS error. The other inputs such as nugget, sill and range were derived from this semivariogram. The nugget represents measurement/independent error and is the deviation from
zero on the y-axis. The sill is the height the semivariogram reaches when it levels off, located on the y-axis, and the range is the distance where the model first flattens out on the x-axis. The interpolated surface and error surface were derived from the analysis.

Validation and cross validation were done for identifying the best interpolated surface. Cross validation technique is based on the “leave-one-out” principle. Interpolate the surface $n$ times, each time leaving one of the points out and then compare the estimated value for the point with the original data points. The test data taken out from the total sample plots were used for validation. The selection of best interpolation method was based on the mean prediction error (equation 4.10) and root mean square prediction error (equation 4.11).

\[
\text{Mean Error (ME)} = \frac{\sum_{i=1}^{n} (\hat{Z}(s_i) - z(s_i))}{n} \quad \text{---------------- (4.10)}
\]

\[
\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{Z}(s_i) - z(s_i))^2}{n}} \quad \text{----------------- (4.11)}
\]

where, $\hat{Z}(s_i)$ is the predicted value and $Z(s_i)$ is the observed value.

**4.4. Results**

The average values of above ground biomass and carbon stock in the whole of Anamalai wildlife sanctuary are 167 tons/ha and 84 tons/ha respectively. Distribution of above ground biomass and carbon stock in different forest types is given in Table 4.1. Evergreen forest showed high amount of biomass (236.8 tons/ha) whereas the thorny scrub showed the low biomass (32.23 tons/ha).
Summation of carbon stock in different forest types yielded a value of 6.44 mega tons of carbon. These forest types covered 80% of the total sanctuary area (see the table 2.1 in chapter 2). The remaining area is not considered in the estimation of carbon stock due to the absence of sample points in non forest area.

Kriging is found to be the best method for the spatial interpolation of carbon stock in comparison with IDW and Polynomial interpolation. The lowest mean error and root mean square error is observed for kriging method in validation and cross validation techniques (Table 4.2). The predicted surface using kriging method is given in Fig. 4.1. The use of locally fitted first order polynomial equation was found to be the second best method.

Table 4.1. Distribution of above ground biomass and carbon stock in different forest types in Anamalai Hills, Western Ghats, India.

<table>
<thead>
<tr>
<th>Forest type</th>
<th>Avg. AGB (tons/ha)</th>
<th>Avg. Carbon stock (tons/ha)</th>
<th>Area (ha)</th>
<th>Total AGB (mega tons)</th>
<th>Total carbon stock (mega tons)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical Evergreen Forest</td>
<td>236.80</td>
<td>118.4</td>
<td>23020</td>
<td>5.45</td>
<td>2.73</td>
</tr>
<tr>
<td>Montane wet temperate forest</td>
<td>187.78</td>
<td>93.89</td>
<td>2180</td>
<td>0.41</td>
<td>0.20</td>
</tr>
<tr>
<td>Tropical Deciduous Forest</td>
<td>141.69</td>
<td>70.85</td>
<td>48760</td>
<td>6.91</td>
<td>3.45</td>
</tr>
<tr>
<td>Thorn Scrub Forest</td>
<td>32.23</td>
<td>16.12</td>
<td>3430</td>
<td>0.11</td>
<td>0.06</td>
</tr>
</tbody>
</table>
Table 4.2 Validation and cross-validation of interpolation methods

<table>
<thead>
<tr>
<th>Interpolation Method</th>
<th>Cross-Validation Mean Error</th>
<th>RMS Error</th>
<th>Validation Mean Error</th>
<th>RMS Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inverse Distance Weighted</td>
<td>-0.069</td>
<td>1.55</td>
<td>-0.194</td>
<td>1.31</td>
</tr>
<tr>
<td>Local Polynomial</td>
<td>0.048</td>
<td>1.48</td>
<td>-0.184</td>
<td>1.33</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>0.004</td>
<td>1.48</td>
<td>-0.144</td>
<td>1.29</td>
</tr>
</tbody>
</table>

4.5. Discussion

The tropical evergreen forest showed the high carbon stock per hectare which could be attributed to the high stand density of these forest. The stand density of montane wet temperate forest (shola) was higher than wet evergreen forest, but its stunted growth in the extreme environmental conditions (such as high elevation and wind) resulted low GBH. Therefore, the allometric equation which is entirely based on GBH calculated lower biomass and carbon stock per hectare of shola forest. The stand density in the thorny scrub forest was extremely lower which resulted least carbon stock contribution in the total carbon stock. Though the carbon stock per hectare of deciduous forest was lower in comparison with evergreen forest, most of the area (~50%) is covered by deciduous forest which in turn resulted high carbon stock contribution in the total carbon stock in the sanctuary. On an overall, the average carbon stock in all these forest types was 84 tons/ha which was slightly higher than the literature value. For example, Chhabra and Dadhwal (2004) estimated carbon stock density in the range of 50-68 tons/ha.
Fig. 4.1. Spatially interpolated surface of carbon stock in Anamalai hills using ordinary kriging technique.

The performance of kriging was better than IDW and first order polynomial equation, however, the maximum value reported in kriging was 5.29 tons/ha which is lower than some of the sample plot values. This is due to the property that kriging is not an exact interpolator and the surface generated will be a function of spatial relationships among the measured values (semivariogram). In case of IDW and local polynomial interpolation, the values were varied from minimum sample plot value (0.13 tons/ha) to maximum sample plot value (7.86 tons/ha) since both techniques are exact interpolators; however, the prediction error was higher in both the methods. Another problem noticed in IDW was it created ‘bulls eyes’ around the measured locations. Though, there were rarely examples of direct
comparison of interpolation techniques in the literature, many studies have used kriging for spatial interpolation. Cheng et al., (2007) used kriging for spatial mapping of above ground biomass, nitrogen and phosphorous in degraded Ordos Plateau grasslands in northwestern China. Spatial distribution pattern of soil microbial biomass carbon in pasture ecosystems in Turkey was interpolated using kriging (Askin and Kizilkaya, 2007).

4.6. Chapter Summary

The biomass and carbon stock in different forest types in the Anamalai wildlife sanctuary is assessed. The point estimates were interpolated to spatial surface using different interpolation techniques. Two types of modelling approaches were taken into consideration. One is deterministic modeling and the other is stochastic modelling. The first approach in the deterministic modelling was to interpolate the point information using similarities between the measured points (Inverse Distance Weighted interpolation). The second approach was to fit a smoothing curve along the measured points (Local polynomial interpolation). In stochastic modelling, ordinary kriging was implemented. The parameters required for kriging were derived from semivariogram. The results showed that the average carbon stock in the sanctuary was 84 tons/ha. The highest carbon stock observed in evergreen forest and the lowest is observed in thorny scrub forest. Spatial interpolation analysis indicated that the mean and RMS errors in the cross-validation and validation steps were lower for kriging. Therefore, Ordinary Kriging could be considered as the best interpolation technique in comparison with IDW and Polynomial interpolation.
4.7. Reference


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