TROPICAL FOREST BIOMASS ESTIMATION AND MAPPING USING *K*-NEAREST NEIGHBOUR (KNN) METHOD

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Commission IV

KEY WORDS: ***K***-nearest Neighbour, Forest, Biomass, Landsat, Map

ABSTRACT:

Estimation and mapping of tropical forest biomass is important for periodic carbon accounting, as tropical deforestation is one of the major sources of terrestrial carbon emission in the recent decades. *K*-nearest neighbour (kNN) method is recently introduced for the estimation of boreal and temperate forest variables from satellite sensors and sample based inventory data. The current study is a first attempt to extend its application to the tropical forest regions. The number of neighbours and feature weighting parameters in the kNN estimation procedure were varied to obtain the optimal precision. The study area was located in the tropical evergreen and semi-evergreen forests of south-eastern Bangladesh. Orthorectified Landsat ETM+ satellite imagery was procured from United States Geological Survey. Atmospheric effect on the image was removed using appropriate correction procedure and digital numbers (DNs) were converted to surface reflectance. Seventy sample plots were laid out in the forests. Diameter at breast height (*dbh*) and heights of all the trees inside the sample plots were measured and later converted to biomass using allometric relations. Forest biomass map was prepared using kNN method entering the optimal parameters and validation was performed using another thirty sample plots. The method is finally recommended for estimation and wall-to-wall mapping of tropical forest biomass.

1. INTRODUCTION

1.1 Background

Estimation of forest variables is important for foresters, as they need to make managerial decisions of the resources under his jurisdiction. Periodic monitoring of growing stocks is useful as well to account the carbon budgets in forest ecosystems. Recently, it becomes increasingly growing concern due to the threat of global climate change. Ground sampling is a traditional method of forest inventory, but has limitations in large-scale application. With the advancement of satellite technology we have the opportunity to combine remote sensing and ground survey to increase the sampling efficiency both in finance and time.

A number of methods are currently available to combine remote sensing and terrestrial sample-based inventory data. Regression is widely used in many studies, where digital number, radiance or reflectance was used as independent variable and forest volume, biomass or basal area was considered as dependent variable. The disadvantage of regression is the models need to compute predicted variables regardless the dependence in prediction and often do not correspond to the original dependence of the field variables. Furthermore, this approach is somewhat laborious in practical applications because the models need to derive for every satellite image set (Tomppo, 2005).

K-nearest neighbour (kNN) method is a newly available technique in forestry application. The method is widely used in pattern recognition (Cover and Hart, 1967; Keller *et al.,* 1985) and statistics (Linton and Härdle, 1998). KNN method was first described by Kikki and Paivinen (1987) for forest resources assessments. This is also termed as reference sample plot method as the technique solely depends on the reference samples in the estimation procedure. For the entire set of pixels without associated ground assessments, *k*-nearest neighbour in the spectral image space are determined among those pixels, which coincide with the location of the field samples. The value of the attributes estimated on the ground at the location of *k* nearest pixels are weighted by the distances in spectral image space and assigned to the respective pixels for which no ground information is available.

The kNN method was used in forest inventories for many countries since its inception: Swedish National Forest Inventory (NFI) (Nilsson, 1997; Reese *et al.,* 2003), U.S. Forest Inventory and Analysis (Franco-Lopez and Bauer, 2001; McRoberts *et al.,* 2002), Norwegian NFI (Gjertsen *et al.*, 1999), Radiata pine plantation inventory in New Zealand (Tomppo *et al.,* 1999) etc. Those studies were concentrated in the boreal and temperate forest regions. The aim of the current study is to extend its applications in the tropics. The study area was located in the tropical evergreen and semi-evergreen forest of south-eastern Bangladesh. kNN method offers a variety of computation options including the selection of optimal value of *k*. A number of weighting functions are also available in Euclidean distance. The current study examined all these alternatives to explore the optimal parameters for the estimation of tropical forest biomass.

1.2 Literature Review

Recognizing the scope of satellite imagery to mitigate the need for wall-to-wall mapping of forest variables, the Finnish Forest Research Institute initiated the Finnish Multi-source National Forest Inventory (FMS-NFI) in 1990. Since then, FMS-NFI has made steady progress towards the mapping of forest structure and types. First introduced to forest inventory by Tomppo

(1991), kNN algorithm is today the primary tool for the national forest agencies of several Nordic countries to classify and map forest attributes (Anon, 2006a).

Development work similar to kNN methods in Sweden was started at the Swedish University of Agricultural Science (SLU) around 1992 (Nilsson, 1997). Holmström *et al,* (2002) applied the technique in the boreal forests of central Sweden. A review of several small projects leading up to the nationwide mapping using kNN in Sweden is available in Reese *et al.* (2002).

Though kNN method was first initiated in the boreal forest conditions of Nordic countries, it has also been extended to the several temperate forest regions. McInenry *et al.* (2005) applied the method for estimating forest volume, basal area, mean stem diameter and stand stocking density in the south-west of Ireland. The study used field inventory data, Landsat ETM+ scene and ancillary spatial datasets. Köhl *et al.* (2001) applied the kNN method to estimate timber and non-timber forest attributes. The study area was located in the south-west of Dresden, Germany. The research used 128 bands hyper-spectral data in the wavelength ranges from 400 to 2480 nm. The study estimated and mapped the distribution of stems, timber volume, crown-closure and deadwood.

Franco-Lopez (2001) applied the kNN method for estimation of forest cover type, basal area and volume for Aspen-Birch and Spruce-Fir forests of north-eastern Minnesota, USA. The study tested several variations within the method including distance metric, weighting function, feature-weighting parameters, and number of neighbours. Finally, maps were prepared for basal area, volume and cover type from a three date 18-band composite image using Euclidean distance and feature weighting parameters.

2. MATERIALS AND METHODS

2.1 Description of Study Area and Stand Information

The study area was located in Southern Chittagong of south-eastern Bangladesh. The area corresponds to the selected part of 136/045 Landsat ETM+ scene. The size of the study area was about 300 sq. km (20km x 15km) covering 21°29´to 21°37´ N Latitude and 92°05´ to 92°13´ E longitude (Figure 1). The area enjoys a sub-tropical monsoon climate. Though there are six seasons in a year, three namely winter, summer and monsoon are prominent. Winter is quite pleasant, begins in November and ends in February. Usually there is no fluctuation in temperature, which ranges minimum of 18° C to maximum of 29° C. The maximum temperature recorded in summer is 32° C to minimum 26° C. Monsoon starts in July and stays up to October. The period accounts for 80% of the total rainfall. The average monthly annual rainfall varies from 400-500 mm in monsoon period (June to October) to 100 mm in dry period.

The forests of the study area are classified as tropical wet evergreen and semi-evergreen forest (Champion *et al.,* 1965). In the regional context the Chittagong flora differs from the Eastern Himalayan flora by the absence of Sal (*Shorea robusta*) and from Myanmar by the absence of Teak (*Tectona grandis*). The outstanding feature of the forest is the frequent occurrence of general Dipterocarpus, Quercus and Eugenia (*Syzygium* spp.) (Baten, 1969).

The *Dipterocarpus* are the characteristic of the evergreen stratum. A certain amounts of deciduous species like *Anacardaeous*, *Swintonia* are predominating. Sterculiaceae, *Artocarpus* and *Sygigium* that generally form an important part of the upper canopy are often present. Bamboo appears in certain places where upper canopy is disturbed, which is typically absent in the virgin forests where canes and palms are the main woody monocotyledons. Tree ferns sometimes occur but epiphytes and ground-ferns are frequent. In the shrubby undergrowth Rubiaceae and Acanthaceae are common. In certain places, gregarious occurrence of several *Dipterocarpus* species is observed in the top canopy with a rare occurrence of any other species (Khan, 1979).

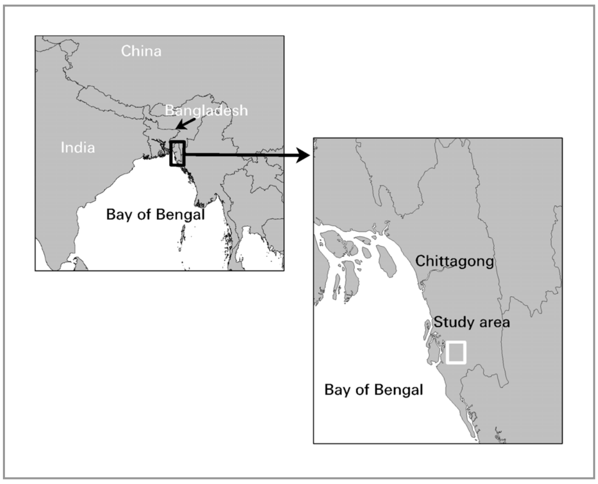

Figure 1. Location of the study area

All the accessible areas were transformed to shifting cultivation and so virgin forests are seldom noticed. Present crop mostly consists of secondary re-growth, which is still in the process of succession to the climax evergreen type. This process of succession is often influenced by the repeated disturbance and thus leads to drier scrubby forests or savannahs in many locations (Khan, 1979). Some areas are invaded by Sungrass (I*mperata arundinaceas*) and Khagra (*Saceftram spontaneum*) (Baten, 1969).

2.2 Selection of Satellite Image

Landsat ETM+ satellite image of 7th February 2001 was selected for the study. The image was chosen on the mid of dry period. This season has an advantage because most of the shrubby undergrowth disappears during this season and does not influence the reflectance of forest canopies. Unfortunately, some deciduous species shed their leaves in these times and consequently their information becomes unavailable on the satellite reflectance acquired in this season. Later image prior to field sampling could not be chosen because of the presence of cloud coverage on the image.

2.3 Image Pre-processing

Orthorectified Landsat ETM+ image was procured from United States Geological Survey (USGS). Non-systematic geometric error was rectified from an identifiable object on the image and measuring the geo-reference information using a handheld GPS. The image was then checked with the other objects and discovered the geometric errors were limited within sub-pixel level.

Atmospheric correction was done by modified dark object subtraction technique, which is termed as COST method (Chavez, 1996). In this process cosine of solar zenith angle was entered as atmospheric transmittance. The technique substantially improved the dark object subtraction (DOS) result. DOS considers the presence of dark objects on the image and their reflectance is the result of atmospheric effect. If this influence is removed from the whole scene a corrected image will be obtained. In this procedure digital numbers (DNs) were converted to surface reflectance.

2.4 Collection of Ground Samples

Field sampling was done during the dry period of 2002-2003 and seventy sample plots were collected. Data from another thirty plots were recorded during 2003-2004 for validation. Eight different vegetation types were identified on the satellite image and the same numbers of strata were constructed using supervised classification. Stratified random sampling was designed to lay out the sample plots. Squared-shaped plot was chosen for inventory. The size of the sample plots was variable depending upon the species class (table 1). Non-destructive sampling approach was applied in our study. Diameter at breast height (*dbh*) and height of the trees inside the sample plots were measured. Seedlings and saplings of lower than 5cm diameter were dropped from the plot, but were measured by locating sub-plot (2mX2m) inside the samples and then normalized.

Table 1. The size of the sample plots

Vegetation type	**Plot size (m^2)**
Primary forest	30X30
Secondary forest	10X10
Old plantation	15X15
Young plantation	10X10
Bamboo	5X5
Shrubs	5X5

2.5 Computation of Plot Biomass

The field measurements were converted to forest biomass using allometric equations. The relations for most of the economically important species were available from Bangladesh Forest Research Institute (Latif and Islam, 1984a; Latif and Islam, 1984b; Latif *et al.*, 1986; Latif *et al.*, 1995). One general equation developed for the mixed species (Latif *et al.*, 1986) was used in our computation for the low-valued timbers. Tree volume was computed and then converted to biomass when no biomass function was available. Wood density ratio was taken from Anon (2006b) and FAO (1997). An average conversion ratio was used in computation for the species of low commercial value.

Specific technique was adapted for bamboo and shrubs. Biomass of bamboo was computed applying the appropriate conversion ratio (Forestal, 1966). For shrubs, a rough estimation technique was applied. Bole volume was computed using the equation for cone (see, Husch *et al.*, 1993), and then converted to biomass applying the average conversion ratio computed from other species. Bole biomass was finally converted to whole plant biomass (above-ground) using the following function (FAO, 1997):

Whole plant biomass = Bole biomass + 0.65 * (bole biomass)……(1)

2.6 Estimation and Mapping of Stand Biomass

The kNN software developed by the Department of Forest Resources, University of Minnesota (Haapanen and Ek, 2001) was used in our estimation. The programs are coded in the DOS-environment so that they can be compiled Unix, Linux or Windows. They are written for the most part in C, but utilize some features of C++. The software needs the unsigned 8-bit digital number and hence reflectance computed in decimal was stretched to unsigned 8-bit prior to starting the kNN estimation.

Seventy field samples and the optical bands of Landsat ETM+ were entered in our analysis. The most variable band was 4 in terms of reflectance of sample plots. No coefficient was used and no limit was set for search radius. K = 1 to 20 and three different weighting factors (equal, inversely proportional to the distance and inversely proportional to the squared distance) were examined.

2.7 Selection of Optimal Parameters

The results were evaluated using the prediction errors computed from independent sample plots, which measures how well a model predicts the response value of a future observation. For every trial, the accuracy of our estimated biomass was examined using the mean squared error (*MSE*), which consists of the systematic and random errors. The difference between the estimated and the actual value is $\Delta_i = \hat{v}_i - V_i$, for the reference plots to derive the variance and bias-component:

$$Var(\Delta) = \sum_{i=1}^{n} (\Delta_i - \overline{\Delta})^2 / (n-1) \quad \text{……………..…..……(2)}$$

$$Bias(\Delta) = \frac{1}{n}\sum_{i=1}^{n} \Delta_i \quad \text{…………..……………………… (3)}$$

$$MSE(\Delta) = Var(\Delta) + [Bias(\Delta)]^2 \quad \text{…………..………...…(4)}$$

Where, V_i is measured biomass of the ith observation and $\hat{v}_i$ is predicted biomass applying the kNN prediction rule.

3. RESULTS AND DISCUSSION

3.1 Optimal Value of *K*

The study estimated the optimal value of k = 6 and *MSE* was 6,432 (figure 2). The value was 17,192 when k = 1. There is a sharp reduction of *MSE* in case of k = 2. Then the graph gently declines and becomes the lowest when k = 6. After that *MSE* slightly starts to increase with the higher values of the nearest neighbours. The increment was not gentle rather abrupt. Therefore, k = 6 was obtained as optimal for the estimation biomass in our study.

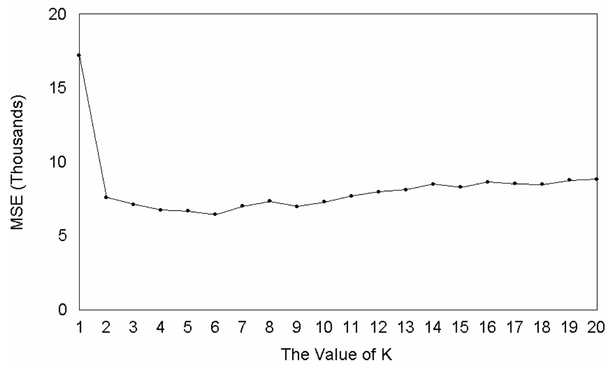

Figure 2. *MSE* and the number of nearest neighbour in kNN estimation procedure

Our finding is quite consistent with many other studies. Holmström *et al.* (2002) applied k = 5 for the estimation of stem volume for the boreal forest of Sweden. McInnery *et al.* (2005) computed k = 3 as optimal for estimating forest volume, basal area, mean stem diameter and stand stocking density in the southwest of Ireland. Franco-Lopez (2001) used k = 1 for the estimation of forest cover type, basal area and volume for Aspen-Birch and Spruce-Fir forests of north-eastern Minnesota.

Some studies obtained the optimal value of k differently. For example, Reese *et al.* (2004) used k = 15 for estimation and mapping of forest volume, height and age for the boreal forest in Sweden. This value was chosen from the previous studies and experience of the Swedish University of Agricultural Science (SLU).

3.2 Weighting Parameters

The results of the three different weighting parameters for biomass estimation are presented in figure 3. Equal weight showed the lowest *MSE* among the three variations examined and it was 6,432. *MSE* gradually starts to increase in case of weights proportional to the inverse Euclidean distance and inverse squared Euclidean distance but the increment was low.

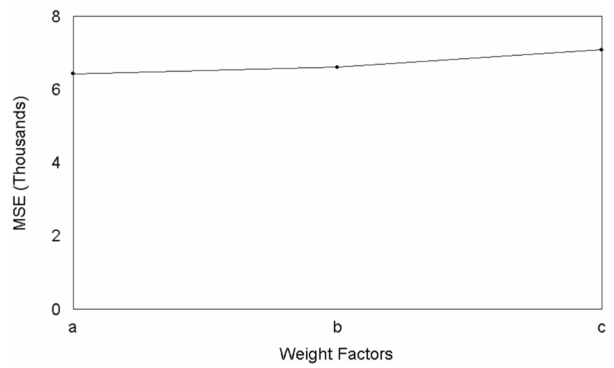

Figure 3. *MSE* and the weighting function in kNN estimation procedure (a = equal, b = inversely proportional to the distance and c = inversely proportional to the square of distance)

3.3 Preparation of Biomass Map

Forest biomass map was prepared using the optimal parameters computed in our study (figure 4). The map shows the biomass level varies from zero to more than 300 Mg/ha (1 Mg = 10^6 gram). The major portions of biomass are concentrated scatteredly in several locations as the forest is distributed. The null biomass is shown in the non-forest region.

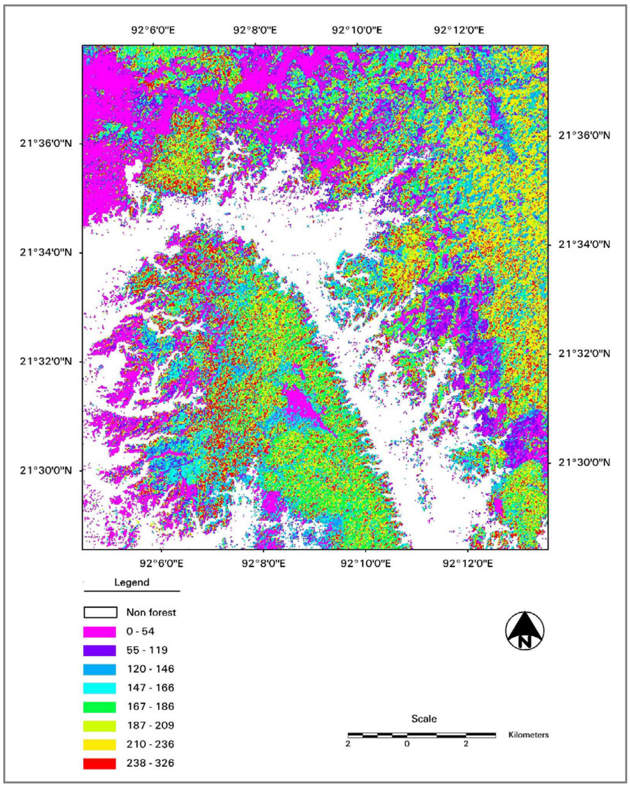

Figure 4. Forest biomass map of Southern Chittagong, Bangladesh

The diagram of validation represents the predicted versus estimated biomass (figure 5). The scatter-plots showing the distribution of observations are concentrated towards the diagonal axis. Some plots are located at the upper part of the diagonal indicates overestimation. These plots content a high amount of green biomass but do not have the proportionate total biomass (green biomass plus branch and trunk biomass). This is a limitation of the optical sensors as they collect information from the top or the first few meters of canopy that obscures to detect the woody biomass stored in the branches or trunks of a tree.

4. CONCLUSION

Reliable assessment of forest biomass in continental and global scale is still a critical part in the climate change research. Lack of suitable methods to combine remote sensing and terrestrial sample based inventory data is the main difficulties in the estimation procedure. KNN method provides a unique opportunity for estimating and wall-to-wall mapping of forest variables. Current study explored the optimal value of nearest neighbour and weighting parameters in the estimation of forest biomass. The value of k = 6 and equal weights provided the best precision in our computation.

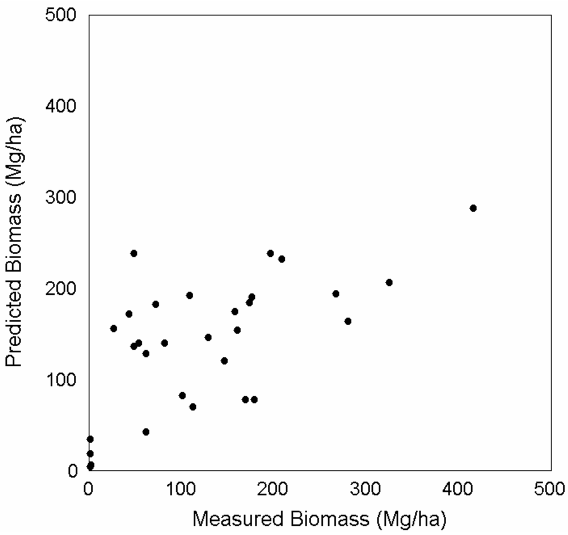

Figure 5. Validation of biomass map for Southern Chittagong Bangladesh

The study faced several limitations. Our research is heavily dependent on the allometrric equations between the directly measured forest variables, *dbh* and height with biomass. Therefore, the accuracy of our estimation depends on the reliability of those relationships. The unavailability of commercial software for the kNN estimation is another limitation. Our research used the software developed by the Department of Forest Resources, University of Minnesota, which can only use unsigned 8-bit as input and output variables. Therefore, we had to stretch the atmospherically corrected reflectance value, which was in float single to unsigned-8 bit. Moreover 255 were the highest value in 8-bit, but our measured biomass was up to 416 Mg/ha. Therefore, we divided our plot values by 2 and then used in our computation and again multiplied the output by the same digit.

Finally, a reliable method of error evaluation in the kNN estimation is not available and Tomppo (1997) reported that a technique was under development. We have to only rely on the cross-validation, where *MSE*, root mean squared error (*RMSE*) or bias is calculated using independent sample plots. Further studies should be carried out to overcome these limitations.

5. ACKNOWLEDGEMENT

I am grateful to Elmar Csaplovics, Dresden University of Technology and Micahel Köhl, University of Hamburg for their comments and suggestions. Landsat ETM+ image was provided by Elmar Csaplovics. I would like to thank Abdul Halim Howlader, Chairman of Bangladesh Space Research and Remote Sensing Organization (SPARRSO) for giving permission to carry out this research. The financial support of Amsterdam Trust Fund to present the paper in ISPRS Symposium is also acknowledged.

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