Correlation analysis between biomass and spectral vegetation indices of forest ecosystem

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Abstract

The forest has an important role in global climatic balance and in maintaining global carbon cycle. The information of forest ecosystem productivity can be assessed through biomass assessment. The forest biomass assessment helps in understanding the resources and the changes in forest ecosystem. Biomass assessment is important since it helps in knowing the amount of carbon sequestered by a forest since 47.5-50% of forest dry biomass is carbon. This study investigates the relationship between above ground biomass and different vegetation indices and to identify the most likely vegetation index that best correlate with biomass. In the present study stratified random sampling were used in the Sindhudurg district for estimation of biomass. A significant correlation was seen between biomass and vegetation indices. The best correlation was assessed and maximum correlation has been found with RVI followed by RDVI, NDVI, OSAVI, MSR and MSAVI with biomass.

Keywords: Biomass, Correlations, Forest ecosystem, Remote sensing, Vegetation indices

1. Introduction

Remote sensing techniques are being used widely for monitoring and estimating vegetation biomass and productivity at large scales (Yamano et al., 2003; Cho et al., 2007; Piao et al., 2007). Biomass assessment has become very important to assess forest ecosystem productivity, determine carbon (C) budgets, and support studies of the role of forests in the global carbon cycle (Zianis and Mencuccini., 2004;Somogyi et al., 2006; Hall et al., 2006;). Biomass plays a very important role in global carbon cycle as it is associated with carbon sequestration; it helps in quantifying pools and fluxes of green house gases from the terrestrial biosphere to the atmosphere formed by various land-use and land cover changes (Cairns et al., 2003). Carbon dioxide is an important green house gases which is responsible for global warming and climatic change. Forest ecosystem plays a vital role in stabilizing global climate, hence studies for the use of forest biomass as sinks for carbon as a part global mitigation effort. Forest ecosystem is one of the major source of storage of carbon in terrestrial ecosystem which constitutes approximately 90% of all living terrestrial biomass (Zhao and Zhou, 2005;Tan et al., 2007;) as a result the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol has recognized forest as the most important in carbon sequestration. The amount of carbon sequestered by a forest can be determined from the biomass since 47.5-50% of forest dry biomass is carbon (Cairns et al., 2003; De Gier, 2003). Biomass assessment is necessary because forest is affected by various factors such as deforestation, fire, harvesting, pests, silviculture and climatic change (Schroeder et al., 1997; IPCC, 2006) which cause changes in the forest ecosystem. However, the quantification of forest biomass becomes difficult due to different approaches, based on field measurements, remote sensing and GIS are available for biomass estimations (Lu, 2006).

The traditional techniques based on field measurements are the most accurate but are difficult to extend over large areas and have proven to be very costly, labour intensive and time consuming (De Gier, 2003). In recent years remote sensing (RS) techniques are being widely used for vegetation mapping and monitoring (Boyd et al., 2003; Ingram, 2005; Lu et al., 2004; Maynard et al., 2007; Dadhwal et al., 2009) which measures the spectral reflectance of the vegetation (Zianis et al., 2005). The spectral reflectances are used for understanding the nature of vegetation characteristics, however it is affected by various factors like vegetation composition, soil characteristics, atmospheric conditions, topography and moisture content (Chen and Wang, 2008). In many studies remote sensing technology has been applied for biomass assessment (Steininger, 2000; Foody et al., 2001; Foody et al., 2003; Lu et al., 2004; Zheng et al., 2004; Muukkonen and Heiskanen, 2005; Maynard et al., 2007; Dadhwal et al., 2009; Kale et al., 2009) because remote sensing has been the only feasible way of acquiring forest information over vast areas at a reasonable cost and acceptable accuracy due to repetitive data collection at a feasible effort (Lu, 2006).

Satellite based vegetation indices (VIs) models are the most commonly used models for estimation of biomass in many studies (Hurcom and Harrison, 1998; Foody et al., 2003; Zheng et al., 2004; Schlerf et al., 2005). Vegetation indices are the mathematical transformation of the original spectral reflectance which are used for interpreting vegetation biomass and cover (Rahman et al., 2003; He et al., 2006; Patel et al., 2007). The fundamental concept in understanding the vegetation indices are based on that vegetation has a high near-infrared reflectance, due to scattering by leaf mesophyll cells and a low red reflectance, due to absorption by chlorophyll pigments which are used in a variety of satellite based vegetation index models for evaluating many vegetation parameters such as leaf area, biomass and other physiological activities (Baret and Guyot, 1991; Verrelst et al., 2008). Vegetation index models use the popular red and near infrared wavelengths to emphasize the difference between the strong absorption of red electromagnetic radiation and the strong scatter of near infrared radiation in knowing the vegetation chacteristic. Vegetation indices (VIs) are used to remove the variations caused in spectral reflectance measurement while measuring biophysical properties caused due to soil background, sun view angles, and atmospheric conditions (Lu, 2006). Many previous studies have shown significantly positive relationship between biomass and vegetation indices (Hurcom and Harrison, 1998; Boyd et al., 1999; Steininger, 2000; Zheng et al., 2004; Heiskanen, 2006; Maynard et al., 2007) however, some results have shown poor relationship (Foody et al., 2003; Schlerf et al., 2005).

Hence a study was taken up to examine the closeness between biomass and vegetation index and to derive correlation equations between biomass and vegetation index in the Sindhudurg district of Maharashtra which is a part of western ghat, an extremely fragile ecosystem and is very sensitive to climate change and human activities (Kale et al., 2009). This study will try to identify the most likely VIs or band ratio that best correlate with biomass.

2. Study Area

The study area shown in figure 1 is a part of Konkan region which is located in the southern west part of Maharashtra. The study area is the Sindhudurg district, which covers a geographical area of 5087 sq. km and located between north latitude 15°37’ and 16° 40’ and east longitude 73° 19’ and 74° 13’. It is covered by forest around 390 sq. km. Sindhudurg district is surrounded by Arabian Sea in the west, Kolhapur district in the east and Goa and Karnataka state in the south. It has semi-tropical climate and remains humid throughout the year. Its average annual precipitation varies from 2300 mm to about 3205 mm. It has minimum temperature of 16.3˚C and maximum temperature of 33.8°C The relief of the district is highly uneven, has a very narrow riverine plains that fringe the coastline and about 40 to 50% of the area in the district is hilly. The forest type of the district is dominated by moist deciduous and semi evergreen forests. The main tree species of the study were Ain (*Terminalia tomentosa*), Jambha (*Xylia dolabriformis*), Kinjal (*Terminalia paniculata*), Sagwan (*Tectona grandis*), Surangi (*Mammea suriga*), Kokam (*Garcinia indica*), Kumbha (*Careya arbprea*), Karmal (*Dillenia pentagyna*), and Hadki (*Rauvolfia serpentina*).

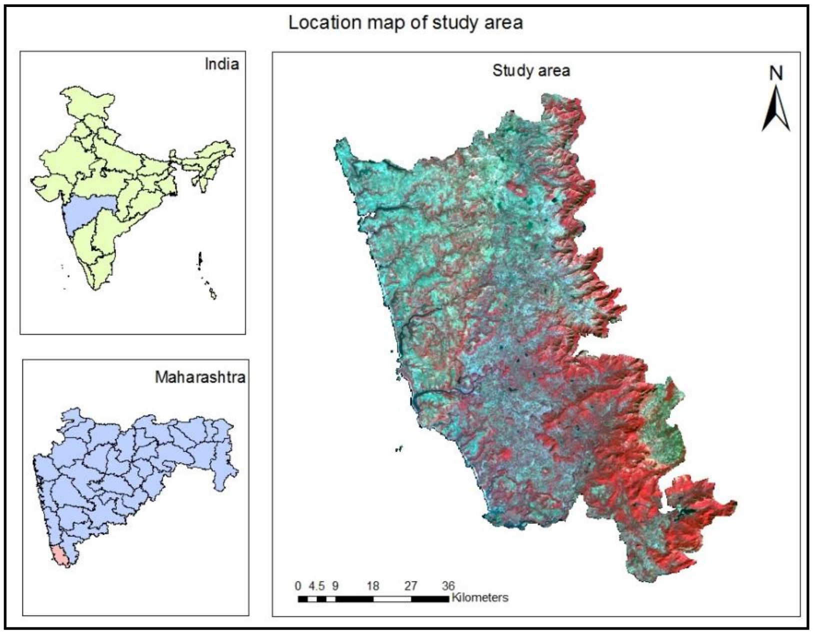

Fig 1: Location map of study area

3. Materials and Methods

In the present study stratified random sampling were used for estimation of biomass in which 33 plots were laid down in different homogenous strata depending on the accessibility of location. The sampling sites were found by using GPSs and Survey of India topo-sheets. The layout of all sampling plots were 30×30m for vegetation, 5×5m for shrubs and 1×1m for herbs, however the plots of shrubs and herbs were within the plot of tree quadrates as shown in Figure 2. The field data collected was in the form of GBH of tree and their heights. Further the biomass of trees are calculated by using biomass equations developed by Forest survey of India (1996) which are related to its biophysical variables such as dbh, height, etc (Zianis et al., 2005).The biomass of each tree was calculated by multiplying the volume by the green wood density and the specific gravity of the tree species. The specific gravity was found using the specific gravities available from book “Method to Estimate dry kiln Schedules”.

Biomass = Specific gravity of wood * volume

The biomass of the plot is then estimated by aggregating the biomass of all the trees, shrubs and herbs.

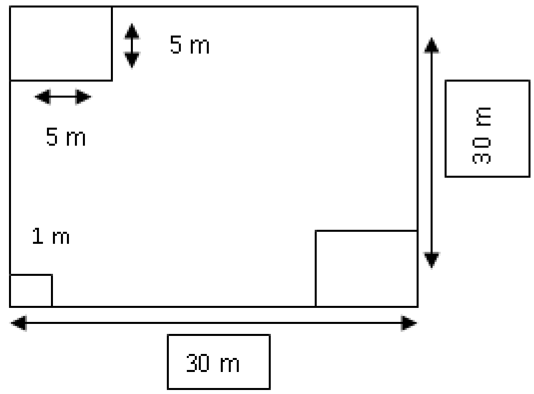

Fig 2: Field plot diagram

The Landsat TM October 2009 satellite data was used in the study. The satellite image was subjected to geometric, atmospheric and topographic corrections. A point shapefile of the sampling sites was generated and overlaid on the corrected image to check the matching plot positions with the ground. The six vegetation indices NDVI, RDVI, MSR, RVI, MSAVI and OSAVI were used to carry out correlation analysis in this study.

3.1 Vegetation Indices

The normalized difference vegetation index (NDVI; Rouse et al., 1974) has been the one of the most commonly and widely used Vis in many forestry applications. The NDVI is the ratio of contrasting reflectance between maximum absorption of red wavelength due to chlorophyll pigments and maximum reflectance of infrared wavelength owing to leaf cellular structure (Paruelo et al., 1997; Rahman et al., 2003; Piao et al., 2007). NDVI has been able to reduce various forms of multiplicative noise such as illumination differences, cloud shadows, atmospheric attenuation, certain topographic variations which are present in different multiple bands (Huete et al., 2002), and however NDVI shows saturation in dense & multi-layered canopy (Tenkabail et al., 2000; Baret and Guyot, 1991; Lillesaeter, 1982).

Therefore substantial efforts were taken in improving and developing new vegetation indices like Renormalized Difference Vegetation Index (RDVI; Rougean and Breon, 1995) and the Modified Simple Ratio (MSR; Chen, 1996) which could linearize the relationships with various vegetation biophysical variables. RDVI index is a modification of NDVI. RDVI was developed to take the combine advantage of Difference Vegetation Index (DVI = NIR - Red; Jordan, 1969) and the NDVI. MSR was proposed over RDVI since MSR shows more sensitivity to various biophysical parameters. MSR is a combination of (SR = NIR/Red; Jordan, 1969) which is considered more linearly related to biophysical parameters of vegetation. RVI (Richardson and Wiegand (1977) is a simple vegetation index which is calculated by dividing reflectance value of near infrared wavelength by those of red wavelength.

3.2 Soil reflectance adjusted indices

There are number of existing soil adjusted vegetation indices which are used for reducing the effect of soil background reflectance. Qi et al. (1994) developed a modified soil adjusted vegetation index (MSAVI) which replaces the manual adjustment factor L, with a self-adjustment L in the MSAVI equation. Rondeaux et al., 1996 developed another optimized soil adjusted vegetation index (OSAVI) which gave satisfactory results on reduction of soil noise in both low and high vegetation cover conditions. The soil reflectance is dependent on various factors like soil type, soil moisture, organic matter and presence of iron oxide (Hoffer 1978). Dry soils have higher reflectance whereas wet soil exhibit lower reflectance in the visible, near infra red and mid infra red spectrum (Hoffer and Johannsen 1969). The equations of the six vegetation indices are given below in the table 1.

Table 1: Vegetation indices used in this study

Vegetation Index	Equation	Reference
Normalized difference vegetation index (NDVI)	$NDVI = \frac{R_{NIR}-R_{Red}}{R_{NIR}+R_{Red}}$	Rouse et al. (1974)
Renormalized difference vegetation index (RDVI)	$RDVI = (R_{NIR}-R_{Red})/\sqrt{R_{NIR}+R_{Red}}$	Roujean and Breon (1995)
Modified Simple Ratio (MSR)	$MSR = \left(\left(\mathrm{R_{NIR}}/\mathrm{R_{RED}}\right)-1\right)/\left(\left(\mathrm{R_{NIR}}/\mathrm{R_{RED}}\right)^{1/2}+1\right)$	Chen (1996)
Ratio vegetation index (RVI)	$RVI = \frac{R_{RED}}{R_{NIR}}$	Pearson and Miller (1972)
Modified soil adjusted vegetation index (MSAVI)	$MSAVI = \frac{1}{2}\left[2R_{NIR}+1-\sqrt{(2R_{NIR}+1)^2 \quad -8(R_{NIR}-R_{RED})}\right]$	Qi et al. (1994)
Optimized soil adjusted vegetation index (OSAVI)	$OSAVI = (1+0.16)(R_{NIR}-R_{Red})/(R_{NIR}+R_{Red}+0.16)$	Rondeaux et al. (1996)

Note: R_{Red} and R_{NIR} in the equations represent the spectral reflectance at the wavelength of red and near-infrared regions, L = 0.5 is a soil adjustment factor to reduce the soil background effect (Qi et al., 1994).

4.0 Results and Discussion

4.1 Biomass calculations

The biomass assessment was done using the field inventory data. The volumetric equations developed and compiled by FSI (1996) were used in tree biomass estimations. Tree volume was multiplied with respective specific gravity of tree species to obtain biomass of trees. The samples of shrubs and herbs were kept inside the oven to obtain dry weight which constitutes the biomass of shrubs and herbs respectively. The sum of biomass of trees, shrubs and herbs were taken as total above ground biomass of sampled designed plot.

4.2 Comparative correlation analysis of above ground biomass and vegetation indices

A comparative correlation analysis was done to check the relationship between vegetation indices and biomass data measured in field. The results shown in figure 1,2,3,4,5 & 6 indicate that that all vegetation indices NDVI, RDVI, MSR, RVI, MSAVI and OSAVI have significant positive correlations with above ground biomass. In linear model the most significant relations was seen in RVI with a R^2 value of 0.785 as visible (Figure 6). The next closer fit was obtained for RDVI. The R^2 value was 0.762 as shown in figure 4. It was observed that the NDVI and OSAVI showed similar R^2 value of 0.750 shown in figure 3 & 8. The R^2 value for MSR and MSAVI were 0.703 and 0.676 respectively as shown in figure 5 & 7. From the given analysis and results we can conclude that all six vegetation indices are useful for biomass estimations.

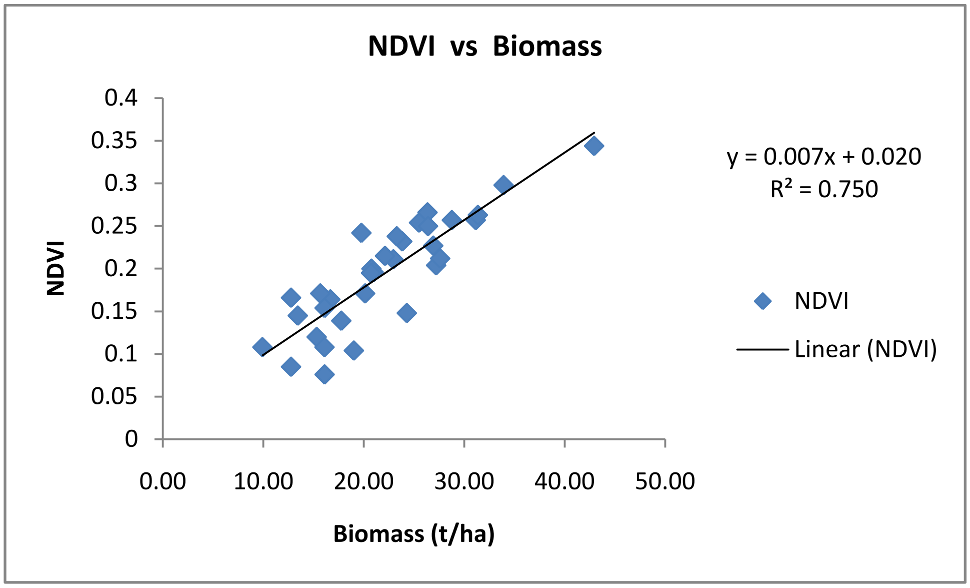

Fig 3: Correlations of aboveground NDVI and biomass

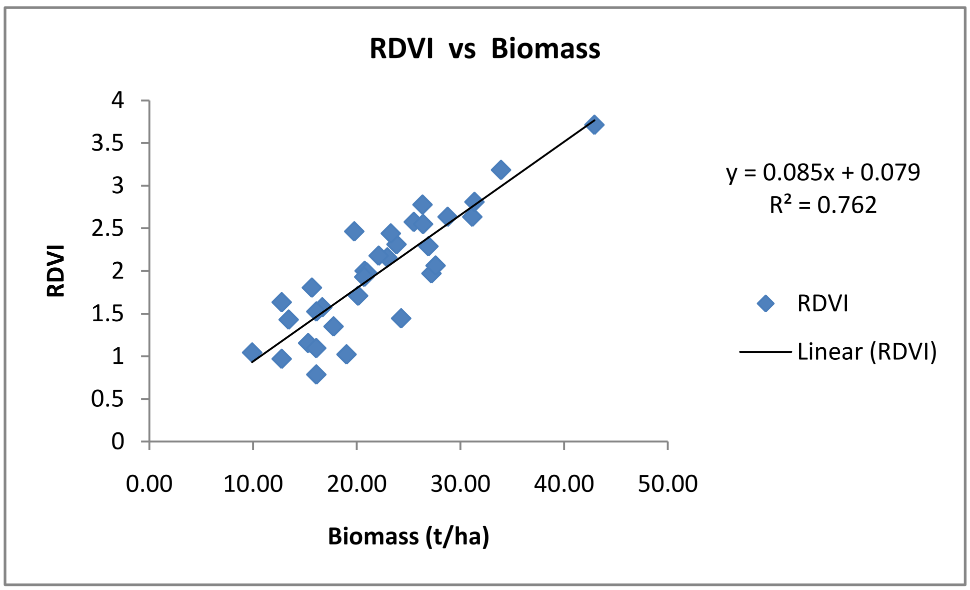

Fig 4: Correlations of aboveground RDVI and biomass

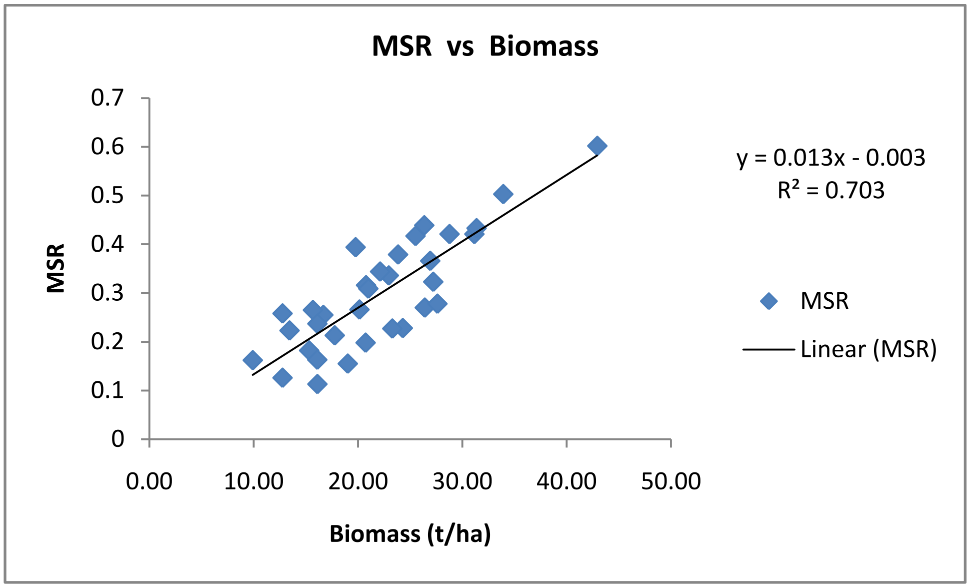

Fig 5: Correlations of aboveground MSR and biomass

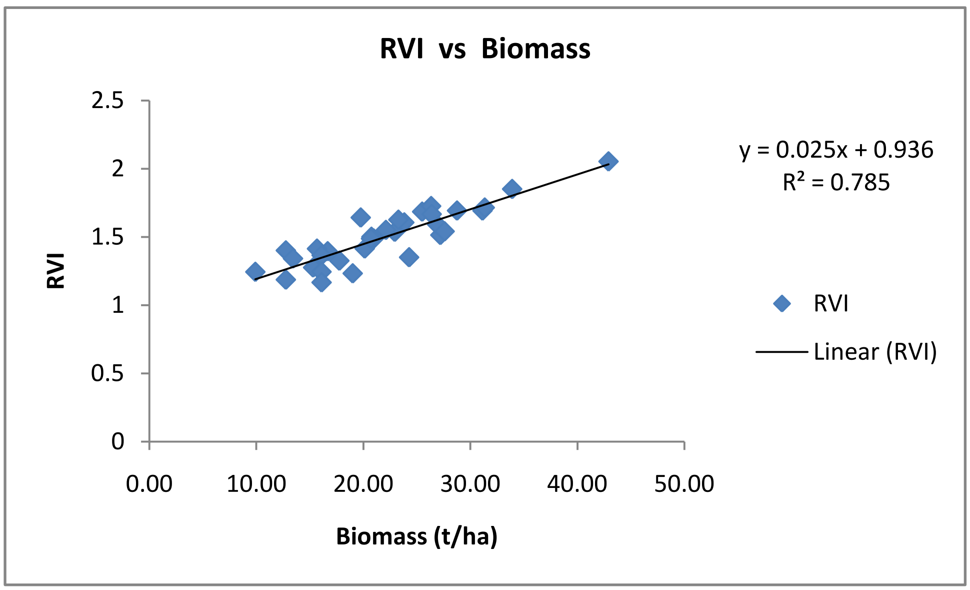

Fig 6: Correlations of aboveground RVI and biomass

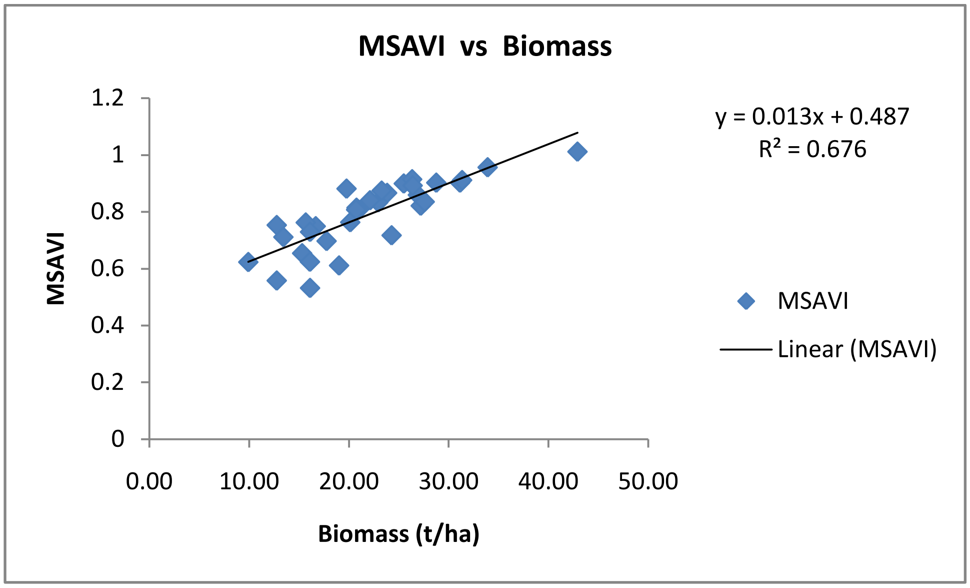

Fig 7: Correlations of aboveground MSAVI and biomass

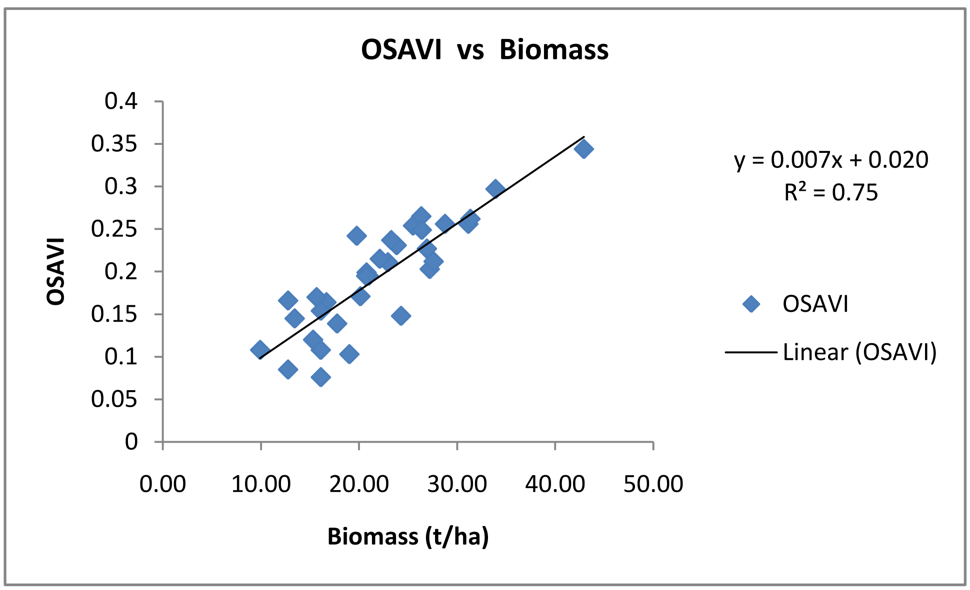

Fig 8: Correlations of aboveground OSAVI and biomass

5.0 Conclusions

The satellite remote sensing methods provides a rapid, efficient and timely estimates of biomass for scientific management of forest resources as compared to traditional approach of biomass assessment based on field measurements which are labour intensive and time consuming. A significant correlation was found between biomass and vegetation indices. The result of this research shows that RVI has the most significant correlation with biomass and is the most appropriate vegetation index for above ground biomass estimation in western ghat region of Maharashtra. These sites most likely had large amount of photosythetically active vegetation and RVI was more sensitive to the contrast between red and infra red reflectance hence RVI was more highly correlated with biomass as compared to other vegetation indices. The use of the most appropriate vegetation index may vary upon the objective of investigation, geographical locations and type of forests of the studied area, hence a more penetrating study needs to be done to understand the most appropriate procedures which can be applied in different environments.

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