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Potential of Landsat-8 spectral indices to estimate forest biomass

A.B. Imran*, S. Ahmed

Department of Forestry and Range Management, PMAS Arid Agriculture University, Rawalpindi, Pakistan

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ABSTRACT

Forest ecosystems are among the largest terrestrial carbon reservoirs on our planet earth thus playing a vital role in global carbon cycle. Presently, remote sensing techniques provide proper estimates of forest biomass and quantify carbon stocks. The present study has explored Landsat-8 sensor product and evaluated its application in biomass mapping and estimation. The specific objectives were estimation of above ground biomass and carbon stocks using field data, assessing relationships of Landsat-8 spectral indices and field data and modeling of biomass and carbon stocks based on best linear regression model. Results showed that the highest aboveground biomass and below ground biomass was recorded as 246 t/ha and 64 t/ha whereas the lowest aboveground biomass and below ground biomass was 55 t/ha and 14 t/ha, respectively. Similarly, the highest above ground carbon and below ground carbon (t/ha) were 116 t/ha and 30 t/ha respectively while the lowest above ground carbon and below ground carbon (t/ha) were estimated as 26 t/ha and 6.7 t/ha respectively. Indices computed from Landsat-8 included normalized difference vegetation index, difference vegetation index, soil adjusted vegetation index, perpendicular vegetation index and atmospherically resistant vegetation index. Regarding relationship between aboveground biomass and vegetation indices, the coefficient of correlation (R^2) were 0.67, 0.68, 0.65, 0.58 and 0.23 for normalized difference vegetation index, soil adjusted vegetation index, Perpendicular vegetation index, difference vegetation index and atmospherically resistant vegetation index respectively. The stepwise correlation between aboveground biomass (dependent variable) and five indices (Normalized difference vegetation index; soil adjusted vegetation index; Perpendicular vegetation index; difference vegetation index; atmospherically resistant vegetation index). Among five vegetation indices, only soil adjusted vegetation index was selected in stepwise method, satisfying the criteria and the overall model R^2 was 0.63 and its adjusted R^2 was 0.60. Simple linear regression model between aboveground biomass and single predictor index was better than stepwise regression model with (R^2= 0.68) and (Root mean square error = 33.75 t/ha). Thus, soil adjusted vegetation index was considered best for biomass mapping. The study concluded that Landsat-8 product has considerable potential for biomass and carbon stocks estimation and can be expanded to national and regional forest inventories, modeling and future reducing emission from deforestation and forest degradation+ implementation.

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INTRODUCTION

The phenomenon of increasing atmospheric carbon dioxide and its drastic impacts on climatic patterns is widely recognized (Streck and Scholz, 2006). Climate change and rise in concentration of greenhouse gases are not only limited to industrialization and rapid economic development, but Forests also substantially contribute to this global climate change. Forests act as carbon stockpile and influence climatic patterns (Denman *et al.,* 2007). Forest ecosystems are among

*Corresponding Author:
Email: *areebimran1996@yahoo.com*
Phone: +92 335 3509135
Fax: +92 51 929214

the largest terrestrial carbon reservoirs on our planet earth thus playing a vital role in global carbon cycle (Ni, 2014; Pravalie, 2018). Deforestation and forest degradation increase carbon dioxide concentration in the atmosphere which acts as major greenhouse gases (Tian *et al.,* 2016) while forest tree growth absorbs the carbon dioxide through photosynthesis (Bellassen *et al.,* 2014; Fares *et al.,* 2017). Forests all over the world are under severe influence of deforestation and forest degradation due to various anthropogenic causes. As global level forests holds the largest stock of terrestrial carbon that is stored in living trees. Reforestation and afforestation activities will enhance the carbon stock to mitigate the adverse impacts of climate change. Prentice *et al.* (2000) worked on the greenhouse gases (GHG) increased by anthropogenic activities and found that carbon dioxide (CO_2) is the most drastic agent causing climate change. Forest plantation act as carbon sink by storing carbon through photosynthesis. Reducing emissions from deforestation and forest degradation (REDD+) is an initiative to reduce the deforestation and carbon emission from forest ecosystems in developing countries. REDD+ implementation requires proper estimates of forest biomass and quantifying carbon stocks so that we can arrive at conclusion whether the forest act as sink or source. A forest is a source when emissions exceeds sequestration and is a sink when carbon absorbed is greater than emitted. Forest biomass can be estimated through different methods using destructive or non- destructive sampling (Gibbs *et al.,* 2007). The destructive method is limited to small areas because it is expensive and harvesting of all trees is not possible for large areas, however, it can be used for developing biomass equation for large forest areas (Segura *et al.,* 2005; Navar 2009). Non-destructive sampling methods involves various forest attributes measurements and biomass assessment through different allometric equations (Ismail *et al.,* 2018). Allometric equations are used to assess the above and below ground biomass and carbon stocks of forest (Ryan *et al.,* 2011). The forest carbon measurement and monitoring system include the traditional forest inventories to estimate biomass and changes in stocks which has many limitations. Currently, remote sensing is the most important part of these monitoring systems and act as major decision support tool for forest managers. The remote sensing technologies have minimized the problems and constraints associated with field data collection to a large extent. Landsat-8 is a multispectral imagery with medium spatial resolution which is one of the most suitable open source sensors for extracting land cover and forestry application. Landsat-8 has fine spectral resolution, high resolution (15 meters) in panchromatic band, 30 meters in multispectral imagery and radiometric resolution of 12bits (Lazaridou and Karagianni, 2016). Gasparri *et al.,* (2010) and Hansen *et al.,* (2013) reported that Landsat are widely for forest mapping, monitoring and biomass assessment at global, regional and local scales. Gizachew *et al.,* (2013) reported that applications of Landsat satellite products are boundless and is used most extensively for biomass and vegetation analysis due to its free data availability, spatial coverage and high temporal resolution. Many previous researches have used Landsat product for biomass estimation through developing relationships between field data and different vegetation indices (Nelson *et al.,* 2000; Foody *et al.,* 2003; Lu 2005). Many researchers worked on Landsat data and explore the behavior of various spectral indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI) (Carreiras *et al.,* 2006; Gizachew *et al.,* 2013; Zhu and Liu, 2015). Ali *et al.,* (2018) have used Landsat-8 and Sentinel-2 products for quantifying above ground biomass in Sub-tropical Scrub forest in Pakistan. The study has explored different vegetation indices (NDVI, SAVI, MASVI) and ground based biomass estimation. The NDVI was considered best spectral index comparatively and was biomass modeling. The present research has explored Landsat-8 sensor product and evaluated its application in biomass mapping and estimation. The specific objectives were; 1) estimation of above ground biomass and carbon stocks through forest inventory 2) evaluation of Landsat-8 spectral bands and indices for estimation of biomass and 3) modeling of biomass and carbon stocks based on best linear regression model. This study has been carried out in District Mansehra, Pakistan in 2018.

MATERIALS AND METHODS

The study area

The Forest are situated between 34^0-$23^/$ and 34^0- $47^/$ north latitudes and 72^0-$59^/$ and 73^0-$14^/$ east longitude (Fig. 1). The tract is rough and mountainous

and the altitude varies from 3,000 feet to 7,300 feet above mean sea level. The tract is hilly and, therefore, the climate varies from place to place depending upon altitude. Generally the summers are moderate, while the winter is intensively cold. Pure Chir Forests prevail throughout the tract dealt within forests of Shinkari. These forests occupy an altitudinal zone between 3000 and 5500 feet, extending up to nearly 7000 feet. The best Chir crops are however found between 3000' to 5000' elevation. Above this altitude the quality of Chir trees begin to deteriorate and is replaced at higher elevations by Blue pine (*Pinus wallichana*). The underwood is scanty and comprises *Rhododendron arboretum*, *Quercus incana*, *Quercus glauca* and *Pyrus passia.* The surveyed area in all these compartments comprised of almost pure mature and sub-mature Chirpine (*Pinus roxburghii*) trees with occasional broad leaved specie *Quercus incana* in the moist nullahs (Working Plan, 2012).

Forest inventory

Circular plots of 0.1 ha were randomly selected in the Sub-tropical Chirpine forests (Pinus roxbughii) and all trees inside the radius of 17.84 m (circle) were measured. During plot layout and measurement was conducted as per statistical principles (coverage and randomness) and accuracy (Molto *et al.,* 2013; Ali *et al.,* 2018). Diameter at breast height (DBH) and height are key variables for estimation of biomass and carbon stocks. DBH was measured with the help of tree caliper and height of trees was measured with Sunnto Clinometer. Sunnto compass was used angle measurement and while measuring tape was used for distance measurement within the plot and between plots. Keeping in view the sampling protocol (Nizami, 2009), all trees with defects (butteressed, swollen portions or forked trees) were also measured.
For the estimation of the tree height, Eq. 1 used.

$$H = D \times [(\tan(\alpha) \pm \tan(\beta)] \quad (1)$$

Where, H = Tree height in meters
α =angle between tree top and observer
β = angle between tree base and observer
D = distance between observer and tree

Allometric Eq. 2 was used to covert DBH and height data to estimate of aboveground biomass (AGB). These equations are regression equations which were used for estimation of tree and biomass based on the relationships between DBH and height (Seidel *et al.,* 2011). These allometric equations were normally developed for specic ecological zone, specific species and site quality (Afzal and Akhter, 2011; Ismail *et al.,* 2018). The allometric equation was taken from Pakistan Forest Institute (PFI), Peshawar, Pakistan (Ali, 2015).

$$Y= 0.0224 * (D^2 *H)^0.9767 \quad (2)$$

Where, Y is the above ground biomass in kilograms
D is Diameter at Breast Height in centimeters
H is height in meters (m)

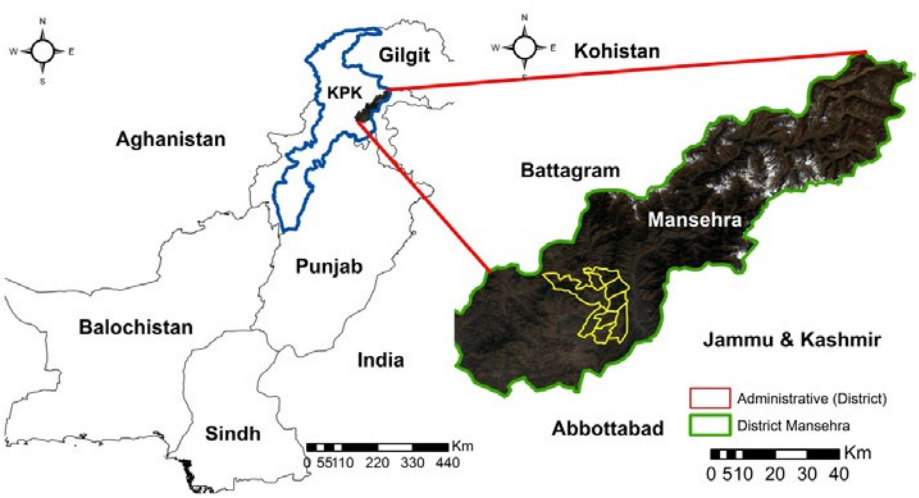

Fig. 1. The geographic location of the study are in district Mansehra, Pakistan

The total AGB of each plot was plot was determined by adding the AGB of all trees in each plot. Thus the AGB per plot were converted into AGB/ha by multiplying it with 10 and divide the resultant by 1000. Malhi *et al.* (2004) considered that about half of the dry biomass consists of carbon. Then above ground carbon (AGC) was determined by multiplying it with 0.47 (Paustian *et al.,* 2006). The AGB and AGC values was then converted into below ground biomass (BGB) and below ground carbon (BDC) by multiplying above ground values with 0.26.

Landsat-8 image processing

It includes satellite data acquisition, per-processing (stacking, mosaic, atmospheric correction, image enhancement, pan sharpening etc.) and image post-processing techniques resulting in information about biomass and carbon stock. Landsat 8 image consist of eleven spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. The resolution for Band 8 (panchromatic) is 15 meters and for Bands 10, 11 are 100m. The Landsat-8 Product was downloaded from USGS Earth Explorer (path: 150, row: 36). The image was acquired for the time of forest inventory and cloud cover of the image was less than 5% with level processing 1T - Standard Terrain Correction (systematic radiometric and geometric accuracy) and projection information: UTM, zone 34, spheroid and datum WGS 84. The preprocessing was the first step before using Landsat 8 image for estimation of biomass. The preprocessing included radiometric calibration, reflectance correction and dark subtraction. Further, the preprocessed image was used to compute various indices such normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), perpendicular vegetation index (PVI), atmospherically resistant vegetation index (ARVI) and difference vegetation index (DVI) (Ali *et al.,* 2018). The details of all vegetation indices are summarized in Table 1. Image subset was made for the study area and the AGB point data was imported on these indices and the values of masked pixels was extracted.

Statistical analysis

The correlation and regression analysis were performed extracted pixel values of vegetation indices and its corresponding biomass data (from field). Regression model (simple and stepwise) were developed based on vegetation indices and above ground biomass using satellite data. In forest inventory data 70% of the data will be used for calibration and 30% for validation purpose. Different linear models were developed namely linear, exponential, power, logarithmic and polynomial. Each model was assessed by coefficient of determination (R^2) and significant value (P-value) and Root Mean Square Error (RMSE). The final model for biomass estimation and mapping have highest coefficient of determination (R^2), least P-value and least Root Mean Square Error (RMSE).

RESULTS AND DISCUSSION

Forest biomass and carbon stocks

The field data was converted into above ground biomass (t/ha), below ground biomass (t/ha), above ground carbon (t/ha) and below ground carbon (t/ha). All of them are summarized in Table 2. The highest AGB and BGB was recorded as 246 t/ha and 64 t/ha in plot 4 whereas the lowest was recorded in plot 19 with AGB and BGB 55 (t/ha) and 14 (t/ha) respectively. The mean AGB and BGB was found to be 121 t/ ha and 31.60 t/ha respectively. Regarding carbon stocks, the highest AGC and below ground carbon (BGC) (t/ha) were 116 t/ha and 30 t/ha respectively while the lowest AGC and BGC (t/ha) were estimated as 26 t/ha and 6.7 t/ha respectively. The mean AGC and BGC was found to be 57.13 t/ ha and 14.85 t/ha respectively. The results was in consistency with AGB of 252 t/ha and 50.46 t/ha reported by Shaheen *et al.,* (2016). While in Sub-tropical Chirpine forest in Ghora Gali,

Table 1. Vegetation Indices for Landsat-8 Product

Indices	Landsat-8	Original Author
Normalized Vegetation Index (NDVI)	(B5- B4) ÷ (B5 + B4)	Rouse *et al.,* 1973
Soil Adjusted Vegetation Index (SAVI)	((B5 - B4) ÷ (B5A + B4 + 0.5)) × (1+0.5)	Qi *et al.,* 1994
Difference Vegetation Index (DVI)	(B5 - B4)	Jordan 1969
ARVI- Atmospherically Resistant Vegetation Index	(ρB8A - ρB4-(ρB2 - ρB4))/(ρB8A+ ρB4-(ρB2 - ρB4))	Kaufman and Tanre, 1992
Perpendicular Vegetation Index (PVI)	(a × B5 - B4 + b) ÷ sqrt(a^2 +1)	Perry and Lutenschlager (1984)

Pakistan, the Amir *et al.,* (2018) reported the total tree biomass of the young, mature, and overmature stand was 80 t/ha, 343 t/ha and 529 t/ha respectively. The lowest and highest carbon stocks were reported as 40 t/ha and 264 t/ha respectively.

Normalized difference vegetation index (NDVI) and aboveground biomass (AGB)

The Fig. 2(a) shows the scatterplot between AGB values from field data and NDVI values derived from Landsat-8 image. The coefficient of correlation was 0.67 which mean that 67% of field data have been explained by the NDVI-based model while 33% of the data are not explained by this model. However, Landsat- NDVI is a proxy data and this much coefficient of correlation is considered good. The correlation of NDVI was greater than (PVI, ARVI, DVI) and less than SAVI. The Fig. 2 (b) showed that higher forest density was found at central part of the study area moving from North to South. NDVI is one of most extensively

Table 2. Plot wise biomass and carbon stocks

Plot No.	AGB (t/ha)	BGB (t/ha)	AGC (t/ha)	BGC (t/ha)
1	130.17	33.84	61.18	15.91
2	113.99	29.64	53.58	13.93
3	152.66	39.69	71.75	18.66
4	246.94	64.20	116.06	30.18
5	217.16	56.46	102.07	26.54
6	130.17	33.84	61.18	15.91
7	179.71	46.72	84.46	21.96
8	113.99	29.64	53.58	13.93
9	182.87	47.55	85.95	22.35
10	71.28	18.53	33.50	8.71
11	95.89	24.93	45.07	11.72
12	121.98	31.71	57.33	14.91
13	127.63	33.18	59.99	15.60
14	60.19	15.65	28.29	7.36
15	134.92	35.08	63.41	16.49
16	117.82	30.63	55.38	14.40
17	64.76	16.84	30.44	7.91
18	103.9	27.01	48.83	12.70
19	55.37	14.40	26.02	6.77
20	73.21	19.03	34.41	8.95
21	93.97	24.43	44.17	11.48
22	85.32	22.18	40.10	10.43

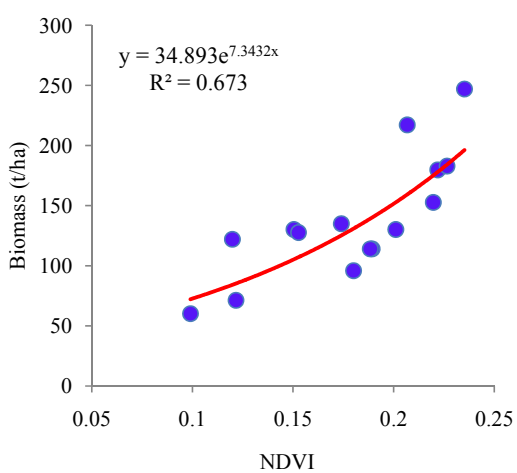

Fig. 2(a). Scatter plot between AGB and NDVI

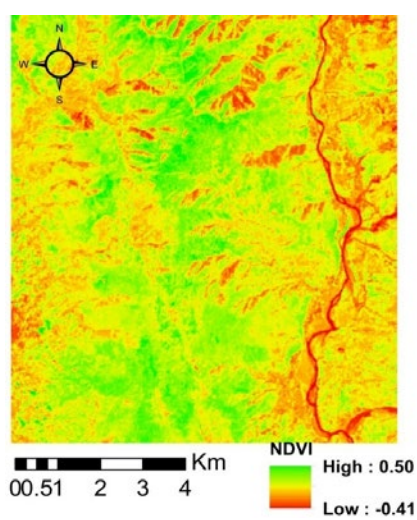

Fig. 2(b). NDVI computed from Landsat-8 Image

used index for vegetation mapping and biomass estimation. Ali *et al.,* (2018) also used Landsat-8 NDVI and correlated it with the field measured biomass and reported coefficient of correlation (R^2= 0.85). While Adan (2018) reported that Sentinel-2 NDVI is a broadband index and it has saturation issues with higher biomass density therefore he reported (R^2=0.1). However, Red-edge NDVI computed has higher coefficient of correlation (R^2= 0.60).

Soil adjusted vegetation index (SAVI) and aboveground biomass (AGB)

The correlation between AGB values from field data and SAVI values derived from Landsat-8 image has been shown in Fig 3 (a). As depicted in the scatterplot, the coefficient of correlation was 0.68 which showed that 68% of field data have been explained by the SAVI model while 32% of the data are not explained by this model. However, the correlation of SAVI with AGB was highest (R^2=0.68) as compared to other indices (NDVI, PVI, ARVI, DVI). The Fig. 3 (b) showed almost similar results, the higher forest density was observed at central part of the study area moving from North to South. The results are in consistency with departmental document of forest inventory (Working Plan, 2012) which also reported high forest was found in the central parts of the study area. SAVI is an improvement to NDVI

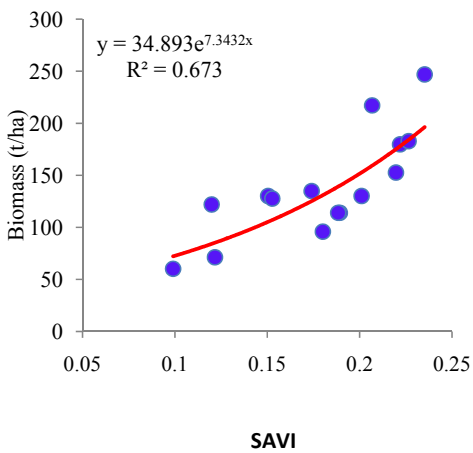

Fig. 3(a). Scatter plot between AGB and SAVI

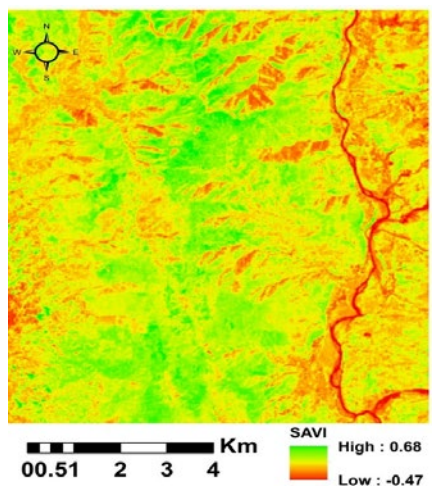

Fig. 3(b). SAVI computed from Landsat-8 Image

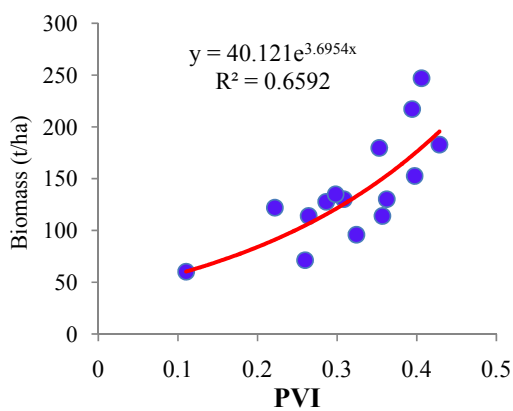

Fig. 4(a). Scatterplot between AGB and PVI

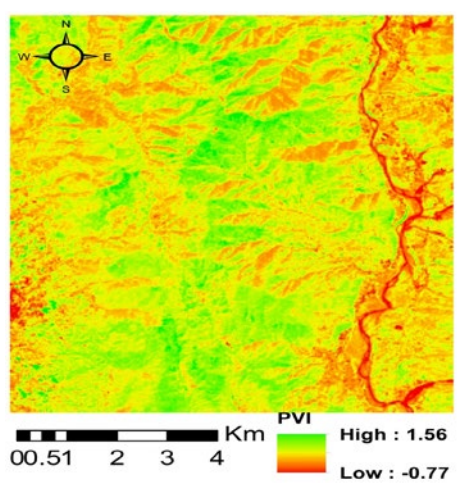

Fig. 4(b). PVI computed from Landsat-8 Image

which enhance vegetation mapping and biophysical properties estimation (Vidhya *et al.,* 2014). Landsat-8 SAVI showed good coefficient of correlation (R^2= 0.85) in study of biomass estimation (Ali *et al.,* 2018). Kumar and Shekhar (2015) reported that SAVI can give good estimation of background soil condition; however, this study showed that SAVI correlation was same as NDVI.

Perpendicular Vegetation Index (PVI) and AGB

The correlation between AGB values and Perpendicular Vegetation Index (PVI) values computed from Landsat-8 image has been shown in Fig 4 (a). As represented in the scatterplot, the coefficient of correlation was 0.65 which showed that PVI model was capable to explain 65% of field data while 32% of the data are not explained by this model. The PVI model has performed well than ARVI and DVI however showed less correlation as compared to SAVI and NDVI. The Fig. 4 (b) showed almost similar results as NDVI and SAVI, the higher forest density was observed at central part of the study area moving from North to South. The results are in consistency with departmental document of forest inventory (Working Plan, 2012) which also reported high forest was found in the central parts of the study area. Kongwongjan *et al.* (2012) integrated PVI with other indices such as NDVI, SAVI and Triangular Vegetation

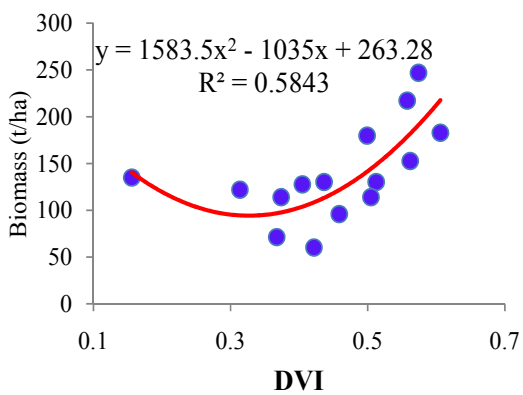

Fig. 5(a). Scatterplot between AGB and DVI

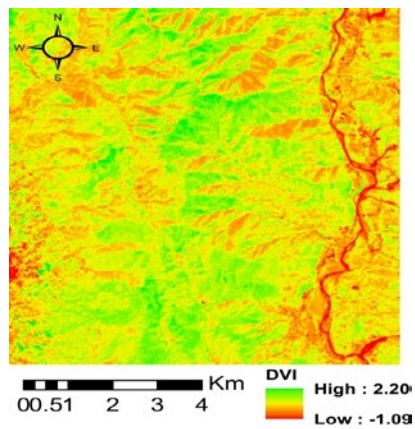

Fig. 5(b). DVI computed from Landsat-8 Image

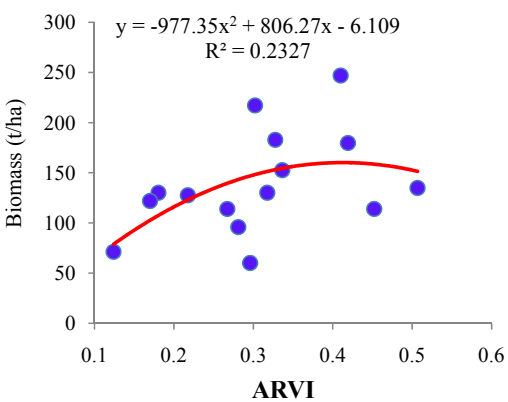

Fig. 6(a). Scatterplot between AGB and ARVI

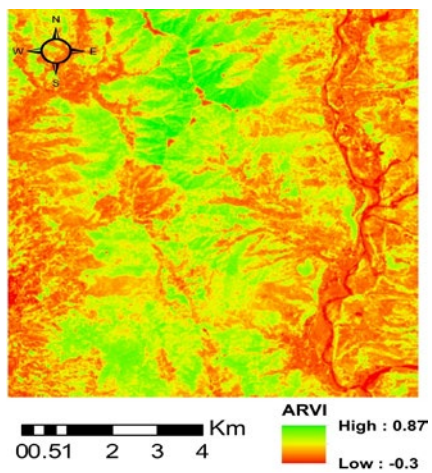

Fig. 6(b). ARVI computed from Landsat-8

Index (TVI) for mapping mangroves forests in Thailand. Ali *et al.,* (2018) reported that Landsat-8 PVI has performed well as compared to Sentinel-2 PVI and reported coefficient of correlation of 0.18 for Sentinel-2 and 0.59 for Landsat-8 respectively.

Difference Vegetation Index (DVI) and AGB

The correlation between AGB values and Difference Vegetation Index (DVI) has been shown in Fig. 5 (a). As illustrated in the Fig. 5 (a), the coefficient of correlation was 0.58 which was showed that DVI has performed less as compared to other indices (NDVI,SAVI, PVI) but it perform well as compared to ARVI. The regression model of DVI can explain 58% of field data variations while 42% of the data variations are remained unexplained. The Fig. 2 (b) showed the DVI values range between 1.09 to 2.20, the higher values showed more vegetation (the higher forest density was observed at central part) while the lower values (1.09) showed lower or no biomass areas such as the eastern part of the study there is no vegetation along the river flowing from north to south. Das and Singh, (2012) studied that relationship between above ground biomass and vegetation indices using Landsat TM image in Ghart region (India) and reported highest correlation (R^2= 0.79 and 0.76) for RVI and Renormalized DVI respectively. Ali *et al.,* (2018) reported good performance of DVI for both Landsat-8 and Sentinel-2 with coefficient of correlation (R^2= 0.59 for Landsat-8 and 0.58 for Sentinel-2 image).

Atmospherically Resistant Vegetation Index (ARVI) and AGB

The correlation between AGB values from field data and Advanced Ration Vegetation Index (ARVI) values derived from Landsat-8 image has been shown in Fig 6(a). As portrayed in the scatterplot, the coefficient of correlation was 0.23 which showed that relationship between ARVI and AGB is not too much strong as compared to rest of the indices (SAVI, NDVI, PVI and DVI). The ARVI regression model can explain only 23% of variation in AGB data while 67 % of the data is not explained by this model. As shown in Fig. 6(b) showed range of ARVI between -0.3 and 0.87; the positive values (0.87 or less) showed vegetation cover while the negative values shows less or no vegetation. The higher forest cover was mapped at central part of the study area moving from North to South as depicted in Fig 6 (b). The results are in consistency with departmental document of forest inventory (Working Plan, 2012) which also reported high forest was found in the central parts of the study area. Previous studies has reported that Ration Vegetation Index can be used for vegetation mapping, biomass estimation and biophysical parameters of vegetation (Das and Singh, 2012; Kumar and Shekhar, 2015; Adan, 2018).

Stepwise linear regression model

The stepwise correlation between AGB (dependent variable) and five indices (NDVI, SAVI, PVI, DVI, ARVI) has been shown in Table 3. Among five vegetation indices, only SAVI was selected in stepwise method, satisfying the criteria of probability-of-F-to-enter <=0.50 and probability-to-remove >= 0.10. The other indices (NDVI, PVI, DVI and ARVI) were removed because their relationship was not significant. The overall model R^2 was 0.63 and its Adjusted R^2 was 0.602 which shows that stepwise regression model of indices explained 63% of the data variations of

Table 3. Stepwise regression model of landsat-8 spectral indices

Variables			Model summary						
Variables entered	Variables removed	Sig	R	R Square	Adjusted R square	Estimate SE	F	Sig.	
SAVI			.794[a]	.630	.602	32.00	22.175	.000a	
	NDVI	.976				Correlations			
	DVI	.814		AGB	SAVI	NDVI	DVI	ARVI	PVI
	ARVI	.978	AGB	1.000	.794	.601	.761	.210	.761
	PVI	.814	SAVI	.794	1.000	.752	.941	.271	.941
Model equation:			NDVI	.601	.752	1.000	.622	.596	.622
			DVI	.761	.941	.622	1.000	-.041	1.000
Biomass = 750.321*SAVI-29.104			ARVI	.210	.271	.596	-.041	1.000	-.041
			PVI	.761	.941	.622	1.000	-.041	1.000

Method:
Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100). a. Dependent Variable: AGB;
a. Predictors: (Constant), savi

Table 4. Accuracy assessment of regression models

Regression type	Dependent variable	Independent variable	Model	R^2	RMSE (t/ha)
Simple Linear	AGB	SAVI	$4003.3x^2 - 922.17x + 133.95$	0.68	33.75
Stepwise Linear	AGB	NDVI, SAVI, PVI, ARVI, DVI	750.321*SAVI-29.104	0.63	47.18

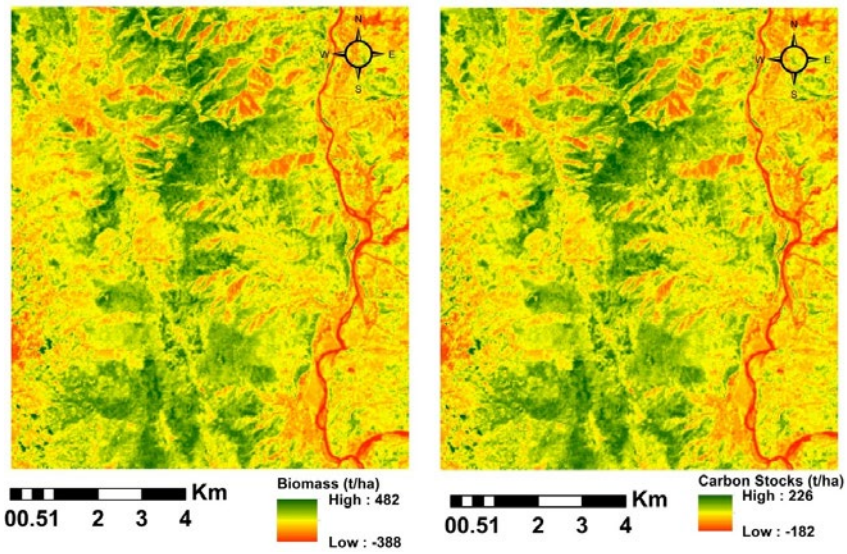

Fig. 7. Biomass and carbon stock estimation using landsat- image

AGB. However, it was found in correlation matrix that strong relationships exist between AGB and spectral indices of Landsat-8. The coefficient of correlation (R^2) for SAVI< NDVI, DVI, ARVI and PVI was 0.794, 0.601, 0.761, 0.210 and 0.761 respectively.

Accuracy assessment of regression models

The accuracy of regression models was evaluated by root mean square error (RMSE). The predicted biomass was estimated by both regression models (simple and stepwise). The final model selection was based on highest Coefficient of Correlation (R^2) and lowest RMSE. As shown in the Table 4, simple linear regression model between AGB and single predictor index (SAVI) was better than stepwise regression model between AGB and all spectral indices. The coefficient of correlation (R^2) and RMSE of simple linear regression model of SAVI was highest (R^2= 0.68) and (RMSE= 33.75 t/ha) respectively.

Biomass mapping

The final biomass map was developed from the best regression model selected between the two models in Table 4 based on RMSE. Thus simple linear regression model of Soil Adjusted vegetation index (SAVI) was considered best for biomass mapping. The above ground biomass and carbon stocks map in Fig. 7 indicated that biomass of study area range between 0-482 t/ha while carbon stocks values range between 0-226 t/ha. The negative values in the Fig. 7 showed no vegetation at the places such eastern and western sides of the study area have no vegetation while the central part has high vegetation.

CONCLUSION

The present research was carried out for the assessment of carbon stocks in *Pinus roxburghii* forest in Siran Forest Division, Pakistan. The findings of the research showed that the highest AGB and BGB was recorded as 246 t/ha and 64 t/ha whereas the lowest AGB and BGB was 55 (t/ha) and 14 (t/ha) respectively. Similarly, the highest AGC and BGC (t/ha) were 116 t/ha and 30 t/ha respectively while the

lowest AGC and BGC (t/ha) were estimated as 26 t/ha and 6.7 t/ha respectively. The study used the state-of-art sensor Landsat-8 for estimation and mapping of biomass and carbon stocks in study area. Various spectral indices were computed from Landsat-8 image. These indices were Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), Soil Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI) and Advanced Ratio Vegetation Index (ARVI). Regarding relationship between AGB and vegetation indices, the coefficient of correlation (R^2) were 0.67, 0.68, 0.65, 0.58 and 0.23 for NDVI, SAVI, PVI, DVI and ARVI respectively. The stepwise correlation between AGB (dependent variable) and five indices (NDVI, SAVI, PVI, DVI, ARVI). Among five vegetation indices, only SAVI was selected in stepwise method, satisfying the criteria and the overall model R^2 was 0.63 and its Adjusted R^2 was 0.602. The accuracy of regression models was evaluated by Root Mean Square Error (RMSE). Simple linear regression model between AGB and single predictor index (SAVI) was better than stepwise regression model between AGB and all spectral indices. The coefficient of correlation (R^2) and RMSE of simple linear regression model of SAVI was highest (R^2= 0.68) and (RMSE= 33.75 t/ha) respectively. Thus Soil Adjusted vegetation index (SAVI) was considered best for biomass mapping. In Pakistan the forests face tremendous pressure regarding fuel wood collection, encroachment, grazing and nuts collection which has deprived the situation of these forests. The finding of the present study revealed that the *Pinus roxburghii* acts as a valuable carbon sink. The proper management, afforestation, reforestation and control of deforestation can enhance the potential of the forest to sequester more carbon so as to combat climate change adverse impacts. The study concluded that Landsat-8 product has considerable potential for biomass and carbon stocks estimation. The Landsat-8 product has comparatively good spatial coverage and medium resolution however, when it is integrated with other sensor data such as Sentinel-2, Sentinel-1 or Synthethic Aperture Redar (SAR) data, the accuracy of biomass estimation can be improved further for national and regional forest inventories and modeling. Therefore the present research has potential applications in integration of Landsat-8 products and national forestry inventory for REDD+ implementation in future.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript. In addition, the ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy have been completely observed by the authors.

ABBREVIATIONS

AGB	Above ground biomass
AGC	Above ground carbon
ARVI	Atmospherically resistant vegetation index
B	Band
BDC	Below ground carbon
BGB	Below ground biomass
DBH	Diameter at breast height
DVI	Difference vegetation index
EVI	Enhanced Vegetation Index
GHG	Greenhouse gases
M	Meters
MSAVI	Modified soil adjusted vegetation index
NDVI	Normalized difference vegetation index
PVI	Perpendicular vegetation index
REDD+	Reducing emission from deforestation and forest degradation
RMSE	Root mean square error
SAR	Synthethic aperture redar
SAVI	Soil adjusted vegetation index
Sqrt	Square root
t/ha	Tonns per hectare
USGS	United Nations Geological Survey
UTM	Universal transverse mercator
WGS84	World Geodetic System 1984

REFERENCES

Adan, M.S., (2017). Integrating Sentinel-2A derived indices and terrestrial laser scanner to estimate above ground biomass/ carbon in Ayer Hitam tropical forest, Malaysia, Master of Science, University of Twente, The Netherlands.

Afzal, M.; Akhter, A.M., (2011). Estimation of biomass and carbon stock: Chichawatni Irrigated Plantation in Punjab, Pakistan." SDPI's Fourteenth Sustainable Development Conference.

Ali, A.; Ullah, S.; Bushra, S.; Ahmad, N.; Ali, A.; Khan, M.A., (2018). Quantifying forest carbon stocks by integrating satellite images and forest inventory data. Aus. J. For. Sci., 135(2): 93–117 **(15 pages).**

Ali, A., (2015), Biomass and carbon tables for major tree species of Gilgit Baltistan, Pakistan, GilgitBaltistan Forests, Wildlife and Environment Department, Gilgit-Baltistan and Pakistan Forest Institute, Peshawar.

Amir, M.; Liu, X.; Ahmad, A.; Saeed, S.; Mannan, A.; Muneer, M.A., (2018). Patterns of biomass and carbon allocation across Chronosequence of Chir Pine (Pinus roxburghii) Forest in Pakistan: Inventory-Based Estimate. Adv. Meteor., 2018, Article ID 3095891., **(8 pages).**

Bellassen, V.; Luyssaert, S., (2014). Carbon sequestration: Managing forests in uncertain times. Nature News, 506(7487): 153.

Carreiras, J.M.; Pereira, J.M.; Pereira, J.S., (2006). Estimation of tree canopy cover in evergreen oak woodlands using remote sensing. For. Ecol. Manage., 223(1-3): 45-53 **(9 pages)**.

Das, S.; Singh, T.P., (2012). Correlation analysis between biomass and spectral vegetation indices of forest ecosystem. Int. J. Eng. Res. Technol., 1(5).

Denman, K.L.; Brasseur, G.; Chidthaisong, A.; Ciais, Ph.; Cox, P.; Dickinson, R.E.; Hauglustaine, D.; Heinze, C.; Holland, E.; Jacob, D.; Lohmann, U.; Ramachandran, S.; da Silva Dias, P.L.; Wofsy, S.C.; Zhang, X., (2007). Couplings between changes in the climate system and biogeochemistry, Chapter 7 in: Climate Change 2007: The Physical Science Basis, The IPCC Fourth Assessment Report, Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Fares, S.; Paoletti, E.; Calfapietra, C.; Mikkelsen, T.N.; Samson, R.; Le Thiec, D., (2017). Carbon sequestration by urban trees. In The Urban Forest. Springer, Cham. 31-39 **(9 pages).**

Foody, G.M.; Boyd, D.S.; Cutler, M.E., (2003). Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sens. Environ., 85(4): 463-474 **(12 pages)**.

Gasparri, N.I.; Parmuchi, M.G.; Bono, J.; Karszenbaum, H.; Montenegro, C.L., (2010). Assessing multi-temporal Landsat 7 ETM+ images for estimating above-ground biomass in subtropical dry forests of Argentina. J. Arid Environ., *74*(10), 1262-1270 **(9 pages)**.

Gibbs, H.K.; Brown, S.; Niles, J.O.; Foley, J.A., (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. Environ. Res. Lett., 2(4): 045023.

Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; Kommareddy, A., (2013). High-resolution global maps of 21st-century forest cover change. Science, *342*(6160): 850-853 **(4 pages)**.

Ismail, I.; Sohail, M.; Gilani, H.; Ali, A.; Hussain, K., Hussain, Karky, B.S.; Qamer, F.M.; Qazi, W.; Ning, W.; Kotru, R., (2018). Forest inventory and analysis in Gilgit-Baltistan: A contribution towards developing a forest inventory for all Pakistan. Int. J. Clim. Change Strategies Manage., 10(4): 616-631 (**16 pages**).

Jordan, C.F., (1969). Derivation of leaf-area index from quality of light on the forest floor. Ecology, *50*(4), 663-666 **(4 pages).**

Kaufman, Y.J.; Tanre, D., (1992). Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. IEEE Trans. Geosci. Remote Sens., 30(2): 261-270 **(10 pages).**

Kongwongjan, J.; Suwanprasit, C.; Thongchumnum, P., (2012). Comparison of vegetation indices for mangrove mapping using THEOS data. Proceedings of the Asia-Pacific Advanced Network, 33: 56-64 **(9 pages).**

Kumar, D.; Shekhar, S., (2015). Statistical analysis of land surface temperature–vegetation indexes relationship through thermal remote sensing. Ecotoxicol. Environ. Saf., 121: 39-44 **(6 pages).**

Lazaridou, M.A.; Karagianni, A.C., (2016, July). Landsat 8 multispectral and pansharpened imagery processing on the study of civil engineering issues. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS Archives, 23rd ISPRS Congress, 12-19 **(8 pages).**

Lu, D., (2005). Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon. Int. J. Remote Sens., 26(12): 2509-2525 **(17 Pages)**.

Malhi, Y.; Baker, T.R.; Phillips, O.L.; Almeida, S.; Alvarez, E.; Arroyo, L.; Chave, J.; Czimczik, C.I.; Fiore, A.D.; Higuchi, N. Timothy J. Killeen; Susan G. Laurance; William F.; Laurance Simon L.; Lewis Lina; María Mercado Montoya; Abel Monteagudo; David A. Neill; Percy Núñez Vargas; Sandra Patiño; Nigel C.A.; Pitman Carlos; Alberto Quesada; Rafael Salomão ; José Natalino; Macedo Silva; Armando Torres; Lezama Rodolfo; Vásquez Martínez John Terborgh; Barbara Vinceti; Jon Lloyd., (2004). The above-ground coarse wood productivity of 104 Neotropical forest plots. Global Change Biol., 10(5): 563-591 **(29 pages).**

Molto, Q.; Rossi, V.; Blanc, L., (2013). Error propagation in biomass estimation in tropical forests. Methods Ecol. Evol., 4(2): 175-183 **(9 pages).**

Navar, J., (2009). Allometric equations for tree species and carbon stocks for forests of northwestern Mexico. For. Ecol. Manage., 257(2): 427-434 **(8 pages).**

Nelson, R.F.; Kimes, D.S.; Salas, W.A.; Routhier, M., (2000). Secondary forest age and tropical forest biomass estimation using thematic mapper imagery: single-year tropical forest age classes, a surrogate for standing biomass, cannot be reliably identified using single-date TM imagery. Bioscience, *50*(5), 419-431 **(13 pages)**.

Ni, Y., (2014). Global potential for carbon storage based on forest ecosystems. Master's thesis.

Nizami, S.M.; Mirza, S.N.; Livesley, S.; Arndt, S.; Fox, J.C.; Khan, I.A.; Mahmood, T., (2009). Estimating carbon stocks in sub-tropical pine (Pinus roxburghii) forests of Pakistan. Pak. J. Agric. Sci., 46(4): 266-270 **(5 pages).**

Paustian, K.; Ravindranath, N.H.; van Amstel, A.R., (2006). IPCC Guidelines for National Greenhouse

Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use Part 2.

Perry, C .Jr; Lautenschlager, L.F., (1984). Functional equivalence of spectral vegetation indices. Remote Sens. Environ., 14(1-3): 169-182 **(14 pages).**

Pravalie, R., (2018). Major perturbations in the Earth's forest ecosystems. Possible implications for global warming. Earth-Science Reviews.

Prentice, I.C.; G.D.; Farquhar, M.J.R.; Fasham, M.L.; Goulden, M.; Heimann, V.J.; Jaramillo, H.S.; Kheshgi, C.; Le Que´re´, R.J.; Scholes, D.; Wallace, W.R., (2001). Pages 183–237 in J. T. Houghton and D. Yihui, editors. Climate change 2001: the scientific basis. The Intergovernmental Panel on Climate Change (IPCC) third assessment report. Cambridge University Press, Cambridge, UK. 183-237 **(45 pages).**

Qi, J.; Chehbouni, A.L.; Huete, A.R.; Kerr, Y.H.; Sorooshian, S., (1994). A modified soil adjusted vegetation index (MSAVI). Remote Sens. Environ. 48: 119–126 **(8 pages).**

Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W., (1973). Monitoring vegetation systems in the Great Plains with ERTS. In: Third ERTS Symposium. NASA, 309–317 **(9 pages).**

Ryan, C.M.; Williams, M.; Grace, J., (2011). Above-and belowground carbon stocks in a miombo woodland landscape of Mozambique. Biotropica, 43(4): 423-432 **(10 pages).**

Segura, M.; Kanninen, M., (2005). Allometric models for tree volume and total aboveground biomass in a tropical humid forest in Costa Rica 1. Biotropica. J. Biol. Conserv., 37(1): 2-8 **(7 pages).**

Seidel, D.; Fleck, S.; Leuschner, C.; Hammett, T., (2011). Review of ground-based methods to measure the distribution of biomass in forest canopies. Ann. For. Sci., 68: 225–244 **(20 pages).**

Shaheen, H.; Khan, R.W.A.; Hussain, K.; Ullah, T.S.; Nasir, M.; Mehmood, A., (2016). Carbon stocks assessment in subtropical forest types of Kashmir Himalayas. Pak. J. Bot, 48(6): 2351-2357 **(7 pages).**

Streck, C.; Scholz, S.M., (2006). The role of forests in global climate change: whence we come and where we go. Int. Affairs., 82(5): 861-879 **(19 pages).**

Tian, H.; Lu, C.; Ciais, P.; Michalak, A.M.; Canadell, J.G.; Saikawa, E.; Huntzinger, D.N.; Gurney, K.R.; Sitch , S.; Zhang, B.; Yang, J., (2016). The terrestrial biosphere as a net source of greenhouse gases to the atmosphere. Nature, 531(7593): 225.

Vidhya, R.; Vijayasekaran, D.; Farook, M.A.; Jai, S.; Rohini, M.; Sinduja, A., (2014). Improved classification of mangroves health status using hyperspectral remote sensing data. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., 40(8): 667.

Working Plan, (2012). Forest Planning and Monitoring Center, Working Plan of Siran Forests, Kyber Pukhtunkhwa, Pakistan.

Zhu, X.; Liu, D., (2015). Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS J. Photogramm. Remote Sens., 102: 222 - 231 **(10 pages)**.

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