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MAPPING AND MONITORING FOREST LANDSCAPE RESTORATION USING LANDSAT-8 IMAGES

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Abstract: *In the context of the Bonn Challenge, Pakistan started Forest Landscape Restoration (FLR) in 2014. This study assessed growth performance and the survival rate of young plantations and developed linear regression models by using Landsat-8 data. The results showed that fast growing species such as Eucalyptus camaldulensis and Robinia pseudoacacia have shown good growth rate as compared to Pinus roxburghii and Cedrus deodara. Landsat-8 vegetation indices include Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Difference Vegetation Index (DVI) and Green Normalized Vegetation Index (GNDVI), which were correlated with volume (m^3). RVI has the highest correlation with R^2 value of 0.88 followed by NDVI, SAVI, and GDVI with R^2 value of 0.83. Stepwise linear regression (SLR) showed that MASVI and SAVI have a strong significant relationship with volume compared to the rest of the indices. Simple linear regression model of RVI and volume has the lowest RMSE (1.19 m^3/ha) and is considered the best for plantation mapping. The temporal assessment of afforestation (2013-2018) by Landsat-8 images showed that plantation was successful in the sampled sites. The RVI differencing and threshold measured area under vegetation was 7,309.7 ha in 2013 and was increased to 9,224.9 ha in 2018. The study suggested that Landsat-8 data have potential for monitoring FLR activities and can be enhanced further when combined with other datasets.*

Key words: *afforestation, growth performance, survival percentage, Landsat-8, vegetation indices.*

1. Introduction

Forest areas throughout the world have been cleared and degraded due to various anthropogenic activities which not only decreased tangible and non-tangible forest benefits but also contributed to climate change. Large scale forest

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restoration and afforestation are needed to combat climate change and rehabilitate forest areas for various functions [40]. About 1.5 billion ha area has been identified for restoration activities and afforestation activities; such restoration are referred to as “mosaics restoration” which can restore productivity, decrease social pressure, alleviate poverty by green income and sustainable forest management [28]. Forest landscape restoration (FLR) is the on-going process of reclaiming ecological functionality and enhancing human well-being across deforested or degraded forest landscapes [28]. FLR has been around since the 1980sbut was globally recognized in 2011 when the German government, the IUCN, and the World Resources Institute (WRI) invited world leaders to initiate forest restoration activities in different countries with the objective of implementing internationally agreed policy objectives, primarily in the land use sector. This agreement was formally named the Bonn challenge [9, 11]. A target of restoring 350 million ha of degraded forest land by 2030 was set in 2014 at the New York Climate summit, whereas the previously assigned target was restoring 150 million ha of land by 2020 [11, 28]. This target is not only similar to the Aichi Biodiversity Target 15 of the Convention of Biodiversity, which aimed at the restoration of 15 percent of degraded ecosystems [8], but it also contributes to the UN goal of enhancing forest carbon stocks through afforestation, reforestation, and forest restoration [43].

In the context of the Bonn Challenge, the Govt of Khyber Pukhtunkhwa (KP) province of Pakistan has shown commitment to the FLR through the Green Growth Initiative (GGI) [21] under which wide-scale afforestation and mosaic restoration were promised. Through GGI, the KP government started large scale afforestation activities in 2014 under a project named “Billion Tree Afforestation Project (BTAP)” and allocated 150 billion USD for forest restoration [25]. BTAP had set a target of 0.35 million hectares restoration by 2018 and additionally thousands hectares plantation were planned throughout the Pakistan [25]. The main goals of BTAP are *(1)* restoration of forest resources and afforestation on degraded areas through participatory forest management, *(2)* generating green jobs, *(3)* combating climate change and its adverse impacts by improving existing forest ecosystems [19]. BTAP planned to plant a billion trees both by planting and natural regeneration and this target was completed in two phases; Phase-I was started in 2014-15 while Phase-II was implemented from 2015 to 2018. Besides forest restoration, BTAP has multifold benefits such as the fact that hundreds of private nurseries have been developed and have generated green jobs (including for young people and women), which has boosted local income and livelihood. The province forest area has been divided into three major circles, i.e., Southern and Central, the Malakand, and the Hazara circles. The BTAP project was implemented throughout the province in all three forest circles. The potential economic and climatic benefits will be 120 million USD and 0.04 $GtCO^2$ sequestrations, respectively. The KP Govt claimed that BTAP will increase the forest area in KPK from 20 to 22%, tree cover from 20 to 30%, and protected areas from 11 to 15%, by 2018 [26].

In addition to field monitoring, the KP forest department has used remote sensing and GIS techniques to validate departmental plantation activities. Despite the importance of forest inventories for reliable estimates and information, they are expensive and tedious. Remote sensing has emerged as an attractive and cost-effective method for various forestry applications, monitoring, mapping, and temporal changes over decades on various scales [3, 35]. Landsat data are widely used for global, continental, regional, and national scales for vegetation research. Landsat-8 has relatively fine spectral resolution, and its free data availability, spatial coverage, and temporal capabilities make it one of the most extensive and boundless used data for vegetation analysis [10]. Various remote sensing techniques have been used for forestry applications, including spectral indices (such as Normalized Difference Vegetation Index, Soil Adjusted Vegetation Index, Enhanced Vegetation Index, etc.), and the spectral band analysis and classification methods [24, 27]. Previously, various studies used remote sensing and geographical information science for afforestation and suitable species selection [12, 14]. Afforestation, landscape restoration, and temporal change detection were assessed by the NDVI differencing technique [32, 37, 39]. This study is advancement to available monitoring data on BTAP activities. We used Landsat-8 temporal images to study the temporal response of vegetation indices computed from these images. The main objectives of the present research are *(1)* to assess the survival percentage and growth rate of afforestation, *(2)* to assess the natural regeneration status within plantation areas, and *(3)* to develop the best linear regression models by integrating vegetation indices and bands to plantation volume (m^3).

2. Materials and Methods

2.1. The study area

The current research was conducted on various plantation sites of District Buner of Pakistan. The district lies between 34^0-10′ and 34°-43′ North latitudes and 72^0-11′ and 72°-49′ East longitudes (Figure 1). The forest types of the area are: dry subtropical broadleaved, pure chir pine (*Pinus roxburghii* Sarg.), dry oak (*Quercus baloot* Griff.), and mixed forests of chir pine (*Pinus roxburghii* Sarg.) and blue pine (*Pinus wallichiana* A.B. Jacks.). The forest inventory for the present study was mainly conducted in chir pine forests. These forests extend from about 1,000 to 1,500 m in elevation. The broadleaved species found in these forests are wild olive (*Olea cuspidate* (Perete. & G. Don) Cif.), sacred fig (*Ficus religiosa* L.), pyrus (*Pyrus pashia* Linnaeus), white oak (*Quercus alba* L.), sticky hop bush (*Dodonaea viscose* Jacq.), hackberry (*Celtis australis* L.), blackberry (*Rubus fruticosus* L.), Monotheca (*Monotheca buxifolia* Falc.), and Malabar Nut (*Adhatoda vassica* L.), etc. Regarding the BTAP activities in district Buner, the plantation activities were conducted in Phase-I (2014-15) as well as Phase-II (2015-17). The total area for afforestation activities was 2,422 ha; out of which 1,130 ha were planted in Phase-I, while in Phase-II an additional 1,292 ha area was afforested. The main target areas were Chamla, Daggar, and Pacha sub-divisions. The main species planted were *Eucalyptus camaldulensis* Dehnh., *Pinus roxburghii* Sarg., *Cedrus deodara* (Roxb.) G.Don., *Robinia* *pseudoacacia* L., and *Alianthus altissima* (Mill.) Swingle.

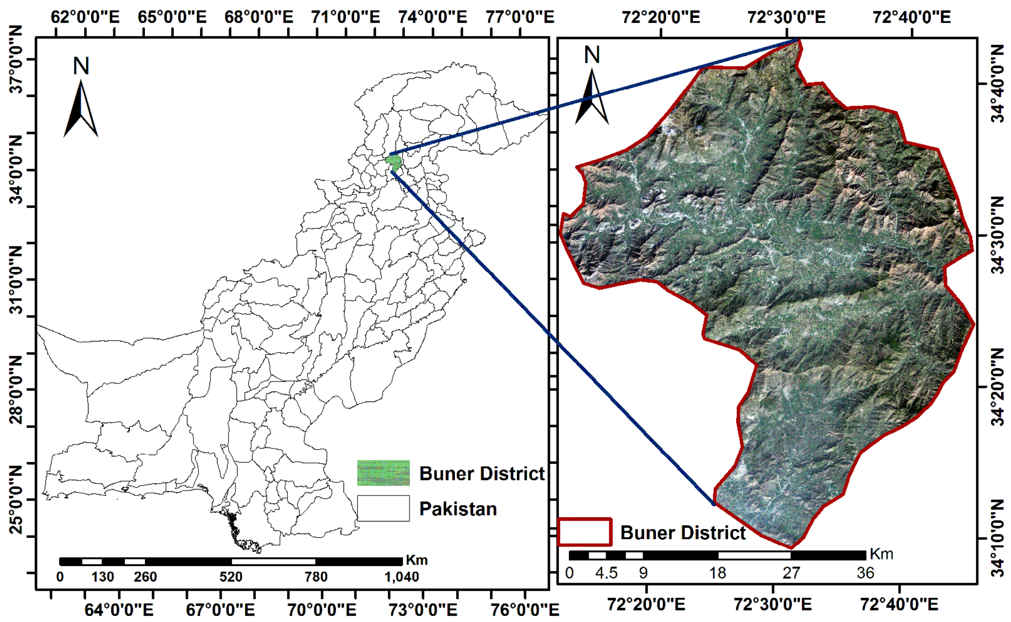

Fig. 1. *Map of the study area*

2.2. Forest Inventory

The simple random sampling technique was used to collect data from the plantation sites. This design was selected for the field measurements because it requires less time, less labor, a low cost, and easy implementation. The names of the selected sites were recorded and the areas were accessed with the help of local Forest Guards. For this purpose, ten sub divisions were selected and circular plots were used for data collection. The total plantation area to be sampled was about 936 ha from which a total of 100 plots were sampled. Firstly, the center point in the plot was located by a GPS receiver and a radius of 17.84 m was measured in all directions followed by an assessment of survival and growth in 5.46 m. All the regeneration inside the circle was counted, followed by height and diameter measurement [3, 34]. Slope correction was made with the help of a clinometer. The height of the trees was calculated with the help of the given formula (Eq. 1):

$$H = \left(\tan\theta \cdot d\right) + a \qquad (1)$$

where:

H is the total height of tree [m];

θ – the angle of tree to the top of the tree from observer's eyes [degrees];

d – the distance between the tree base and the observer [m];

a – the observer eye height [m].

A departmental procedure was adopted for the enumeration of pit density and later it was upscaled area-wise. The average spacing was 10 by 10 feet and a pit density of 1070 was obtained per hectare. Pit density was calculated as (2):

$$N = \frac{D \div 3.28^2}{A} \quad (2)$$

where:

N is the number of pits per hectare;

D – the distance between two plants [feet];

A – the area in square meters.

To know about the success or failure of any planted species, growth and survival of different species were indicators of plantation success [29, 44, 48]. The total number of pits and empty pits in a plot give the overall view of the survival of species as lower empty pits depict higher survival rate. The sowing was also done in the pits and also outside the pits which showed better results. The empty pits were calculated simply by counting. Plot-wise survival rates were determined by Eq. (3) and were upscaled to site by using pit density data and plantation areas.

$$S_p = \frac{N_e}{N_t} \cdot 100 \quad (3)$$

where:

S_p is the survival percentage;

N_e – the number of empty pits per hectare;

N_t – the number of total pits per hectare.

Sowing of various seeds was also carried out in pits either during the plantation operation or after plantation. In addition to planted or sowed seedlings, natural regeneration appeared in areas where conservation activities were conducted. Assisted Natural Regeneration (ANR) was also assessed by counting in areas closed for raising plantations which was a simple and cost-effective restoration approach for FLR [16], because the expenditure on ANR is half compared to other restoration techniques [5]. Height was a key factor to distinguish regeneration establishment. Regeneration was considered established if it had more than nine inches in height and un-established when height was less than nine inches. It was found that five different species were planted under BTAP in the selected sites; therefore species composition was also taken into account. Moreover, polygon data were developed from GPS receiver point data from sites of natural regeneration and the same polygon data was used in temporal assessment using Landsat data. Separate polygon data were developed for forest covered areas in order to differentiate them from grass cover.

2.3. Landsat-8 Image Processing

The remote sensing part used Landsat-8 for BTAP assessment. Landsat 8 has two instruments on board: Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). The Landsat-8 series images were downloaded from USGS website (https://earthexplorer.usgs.gov/) for the years 2013, 2016, and 2018. All the images were acquired with minimum cloud cover because high quality images were selected for spectral indices of BTAP plantations. Landsat-8 was passed through a rectification process to improve its quality. The main preprocessing steps for Landsat-8 were radiometric calibration, reflectance correction, and dark object subtraction [3]. After preprocessing, subsets of the study area were made both from the rectified images to decrease analysis computation time. Based on previous studies, five vegetation indices (VIs) were computed from the rectified images [1, 3].

Among the spectral bands Red and Near Infrared (NIR) Bands were used in VIs. In the case of Landsat-8, Band 4 was Red and Band 5 was NIR. The indices computed from Landsat-8 (2018 image) were used to assess vegetation indices response for model development. Further, the reflectance values for all bands were also extracted from Landsat-8 images. The various spectral indices that were computed for all these images were Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Green Normalized Vegetation Index (GNDVI), and Ratio Vegetation Index (RVI). All indices' formulae and bands are shown in (supplementary file Table 1) and they are used for forest stock assessment, mapping, and monitoring [16, 32].

Vegetation Indices Landsat-8 Product Table 1

Indices	Formula	Original Author
Normalized Vegetation Index (NDVI)	(NIR – R) ÷ (NIR + R)	[2]
Soil Adjusted Vegetation Index (SAVI)	((NIR – R) ÷ (NIR + R + L)) · (1 + L)	[3]
Modified Soil Adjusted Vegetation Index (MSAVI)	1 ÷ 2[2 · NIR + 1 - sqrt((2 · NIR + 1) - 8(NIR - R))	[3]
Ratio Vegetation Index (RVI)	NIR ÷ R	[49]
Green Normalized Vegetation Index (GNDVI)	NIR - B ÷ NIR + B	[4]
Indices	**Landsat-8**	**Original Author**
Normalized Vegetation Index (NDVI)	(B5 - B4) ÷ (B5 + B4)	[2]
Soil Adjusted Vegetation Index (SAVI)	((B5 - B4) ÷ (B5A + B4 + 0.5)) · (1 + 0.5)	[3]
Modified Soil Adjusted Vegetation Index (MSAVI)	1 ÷ 2[2 · B5 + 1 - sqrt((2 · B5 + 1) - 8(B5 - B4))	[3]
Ratio Vegetation Index (RVI)	(B5) ÷ (B4)	[49]
Green Normalized Vegetation Index (GNDVI)	$\frac{\text{B5 - B2}}{\text{B5 + B2}}$	[4]

NDVI is one of the most common indices used for vegetation studies. The output values range from -1 to +1, the negative values represent no plantation and the positive values indicate plantation success. RVI is ratio between NIR and the Red portion of the spectrum because of its importance in photosynthesis. The range of RVI is from 0 to higher positive values; RVI values for bare soils are normally zero, but as the vegetation or greenness increases, the value increases per pixel, thus higher RVI values show more vegetation. The SAVI overcome the soil interference in the reflectance values by considering the soil factor, which is why SAVI can be used in combination with NDVI. MASVI is the modified SAVI, which enhances its spectral rationing quality further. Both SAVI and MSAVI have the same range similarly to NDVI. The plantations shape file created via ArcGIS 10.3 was overlaid on computed VIs of both sensors' images. The masked pixels values were extracted for all the indices and arranged properly in excel sheets. Further, temporal change of afforestation, NDVI differencing, and change over time, were assessed in Landsat-8 [32, 35].

2.4. Statistical Analysis

The statistical analysis was used to assess the relationships of volume (m^3) against bands and indices [7] which include correlation, simple regression with one predictor (indices), and stepwise linear regression. The independent variables for step-wise linear regression were spectral indices and bands which were regressed against dependent volume (m^3). The models were developed using 70% of the field data and 30% data were used for validation purposes. Outliers were removed during model development. The accuracy of the model was evaluated by Root Mean Square Error (RMSE). The model selection was based on highest R^2 value, lowest RMSE, and lowest p-value. The RMSE formula is (4):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Yi - \hat{Y}i\right)^2} \qquad (4)$$

where:
Yi is the measured volume from field data;
Ŷi – the estimated volume predicted from Landsat-8 images;
n – the number of samples.

3. Results and Discussion

3.1. Pit Density and Survival Percentage

Results on pit density of all the plantation sites is summarized in Table 2. Amnawar had the highest number of 400 empty pits per hectare while Char had the lowest number of 26.2 empty pits per hectare. Similarly, Char had the highest survival percentage 97.5%, while Amnawar had the lowest survival rate of 62.7%. Overall, most sites showed excellent survival rate (more than 90%) while few sites (Sulay, Gumbat, Amnawar) had a good performance. When the survival rate was upscaled, to subdivision level, the results in Daggar subdivision showed that the survival rate was of 92.24%, whereas in Chamla Forest Range the survival rate was estimated at 95.28%. The survival rate for *Eucalyptus camaldulensis* Dehnh.m *Pinus roxburghii* Sarg., *Robinia pseudoacacia* L., *Cedrus deodara* (Roxb.) G. Don was 92, 96, 97, and 96%, respectively. Similar findings have been reported by [46], who estimated the survival rate in Daggar subdivision at 94% and in Chamla Forest Range at 95%, while in [47] report phase II the survival rate in District Buner was 82.50%. The success behind this survival rate (95%) was reasoned by supplementing the failed plant pits with new ones and proper maintenance. The data further revealed that there was no significant variation in the survival rate of all selected species. Watanabe et al. [45] reported a survival rate in the range 23.3-97.3% for the *Eucalyptus camaldulensis* Dehnh. plantation. Our results were consistent with FAO findings which reported not only quite high survival rates (91-95%) for *Eucalyptus camaldulensis* Dehnh. in six months, but also recognized *Eucalyptus camaldulensis* Dehnh. and chir pine as suitable exotic tree species for afforestation.

Pit density and survival rate Table 2

Name of Plantation Site	Area [ha]	No of sample Plots	Empty Plots*	Empty/ha	Total No. of pits**	Total Empty pits	Survival rate [%]
Najdara	56	6	19	31.6	60200	1773	97.0
Sulay	24	2	58	290	25800	6960	73.0
Gumbat	58	8	208	260	62350	15080	75.8
Char	79	12	21	26.2	84925	2073	97.5
Shuprang	220	13	43	35.8	236500	7883	96.6
Amnawar	24	4	160	400	25800	9600	62.7
Jubra	120	13	71	64.5	129000	7745	93.9
Ambela Dara	43	9	31	38.7	46225	1666	96.3
Mian Dhand	92	8	35	43.7	98900	4025	95.9
Korea Dara	120	8	52	65	129000	7800	93.9
Gharay Saparay	42	8	65	81.2	45150	3412	92.4
Azghar	58	9	76	84.4	62350	4897	92.1
Total	936	100			1006200		

* Empty plots are total number of empty pits that were counted in all plots
**This total number of pits was calculated @ 1075 per hectare.

3.2. Species Composition and Natural Regeneration

Out of the planted species (*Eucalyptus camaldulensis* Dehnh., *Pinus roxburghii* Sarg., *Robinia pseudoacacia* L., *Cedrus deodara* (Roxb.) G. Don, *Aliantus altissima* (Mill.) Swingle), *Eucalyptus camaldulensis* Dehnh. has the highest share, i.e., 83.80%, followed by *Pinus roxburghii* Sarg. With 14.21%, whereas the percentages of the remaining species (*Robinia pseudoacacia* L., *Cedrus deodara* (Roxb.) G. Don, *Aliantus altissima* (Mill.) Swingle) were 1.6, 0.32, and 0.09%, respectively. *Eucalyptus camaldulensis* Dehnh. was selected for plantation purposes by taking into consideration the priority of the concerned community due to its fast growth, more chances of survival in dry conditions, and quick return [47]. Regarding ANR (data are provided in Table 3), the highest regeneration per hectare (52570) was observed in Amnawari, followed by Sulay and Jubra with 23890 and 21540 individuals per hectare, respectively. While Char, Korea, and Ghagary Sparry had the lowest regeneration, there was no natural regeneration observed in Ambela Dera and Mian Dhand. The composition of natural regeneration was 70% of *Dodonea viscosa* Jacq., 24% of *Acacia modesta* Wall., 5% of *Zizyphus* Mill., 1% *Pinus roxburghii* Sarg., 0.06% *Kamila* L., and 0.012% *Robinia pseudoacacia* L.. Similarly, previous studies reported that *Eucalyptus camaldulensis* Dehnh. species was selected for dry land industrial and rural afforestation [15], greater biomass production [36], as bioenergy crop, and to meet timber requirements [31]. It can tolerate soil salinity problems in denuded lands [22]. However, the percentage of native species (*Pinus roxburghii* Sarg.) should be increased keeping in view the ecological condition of the area. Because excess of *Eucalyptus camaldulensis* Dehnh. may have negative impacts on natural vegetation in the future, Farias et al. [12] reported that the indigenous species (*Tachigali vulgari* L.F. Gomes da Silva & H.C. Lima) should be promoted as compared to the exotic *Eucalyptus camaldulensis* Dehnh. Sajwaj et al. [41] and Miles et al. [33] also reported similar results regarding the exotic species' negative influence on indigenous vegetation.

Table 3

Natural regeneration status

Site	Height [inches]		Total	Average number of Reg/plot	Reg/ha	Total regeneration
	<9"	>9"				
Najdara	6911	4923	11835	1972	19720	1104320
Sulay	1914	2864	4778	2389	23890	573360
Gumbat	5127	3224	8333	1041	10410	603780
Char	0	3	3	0.38	3.8	300.2
Shuprang	974	2551	20738	1728	17280	3801600
Amnawar	11802	9228	21031	5257	52570	1261680
Jubra	13711	9989	23701	2154	21540	2584800

3.3. Growth Performance

The results of species growth data collected in terrestrial measurements are reported in Table 4. The results show river redgum (*Eucalyptus camaldulensis* Dehnh.) has attained an average girth of 4.36 cm and a height of 1.5 m in 19 months, and the average girth and height for chir pine (*Pinus roxburghii* Sarg.) was 6.53 cm and 0.6 m, respectively in 26 months. Similarly, the mean girth and height of black locust (*Robinia pseudoacacia* L.) was 13.88 cm and 3.65 m in 36 months, respectively, while in the case of deodar (*Cedrus deodara* (Roxb.) G.Don), the growth was slow as girth was 3.94 cm and height was 0.70 m in 60 months. The results show that fast growing species including black locust (*Robinia pseudoacacia* L.), tree of heaven (*Ailanthus altissima* (Mill.) Swingle), and river redgum (*Eucalyptus camaldulensis* Dehnh.) performed well and were considered suitable for social forestry programs. In contrast, coniferous species are slow growing species and are suitable for enclosures within natural forests.

Leslie et al. [29] reported similar height growth for river redgum (*Eucalyptus camaldulensis* Dehnh.) and found 0.5, 1.4, 1.5, 2 m height in 5, 14, 29 months, respectively. [38] evaluated the monthly diameter and height growth of river redgum (*Eucalyptus camaldulensis Dehnh.*) over 12 months. Diameter increment was recorded from 3.35 cm to 10.27 cm and height increment was from 2.15 to 6.56 cm.

Age wise growth rate of different species Table 4

Species	Site	Age [months]	Girth at base [cm]	Height [m]
Eucalyptus camaldulensis	Shuprang	7	1.8	0.75
Eucalyptus camaldulensis	Jubra	8	1.67	0.78
Eucalyptus camaldulensis	Gumbat	13	2.10	0.94
Eucalyptus camaldulensis	Amnawar	14	1.73	0.68
Eucalyptus camaldulensis	Azghar	20	3.79	1.69
Eucalyptus camaldulensis	Najdara	27	5.98	1.80
Eucalyptus camaldulensis	Mian Dhand	28	3.88	1.52
Eucalyptus camaldulensis	Korea Dara	31	5.01	1.91
Eucalyptus camaldulensis	Ambela Dara	37	10.49	3.13
Eucalyptus camaldulensis	Sulay	50	11.54	3.07
Ailanthus altissima	Jubra	28	6.50	1.75
Pinus roxburghii	Shuprang	14	1.54	0.34
Pinus roxburghii	Amnawar	21	1.98	0.41
Pinus roxburghii	Najdara	34	8.78	0.50
Pinus roxburghii	Mian Dhand	35	5.93	0.72
Pinus roxburghii	Ambela Dara	44	10.18	0.93
Cedrus deodara	Char	60	3.94	0.70
Robinia pseudoacacia	Jubra	28	9.9	2.37
Robinia pseudoacacia	Char	38	14.87	3.97

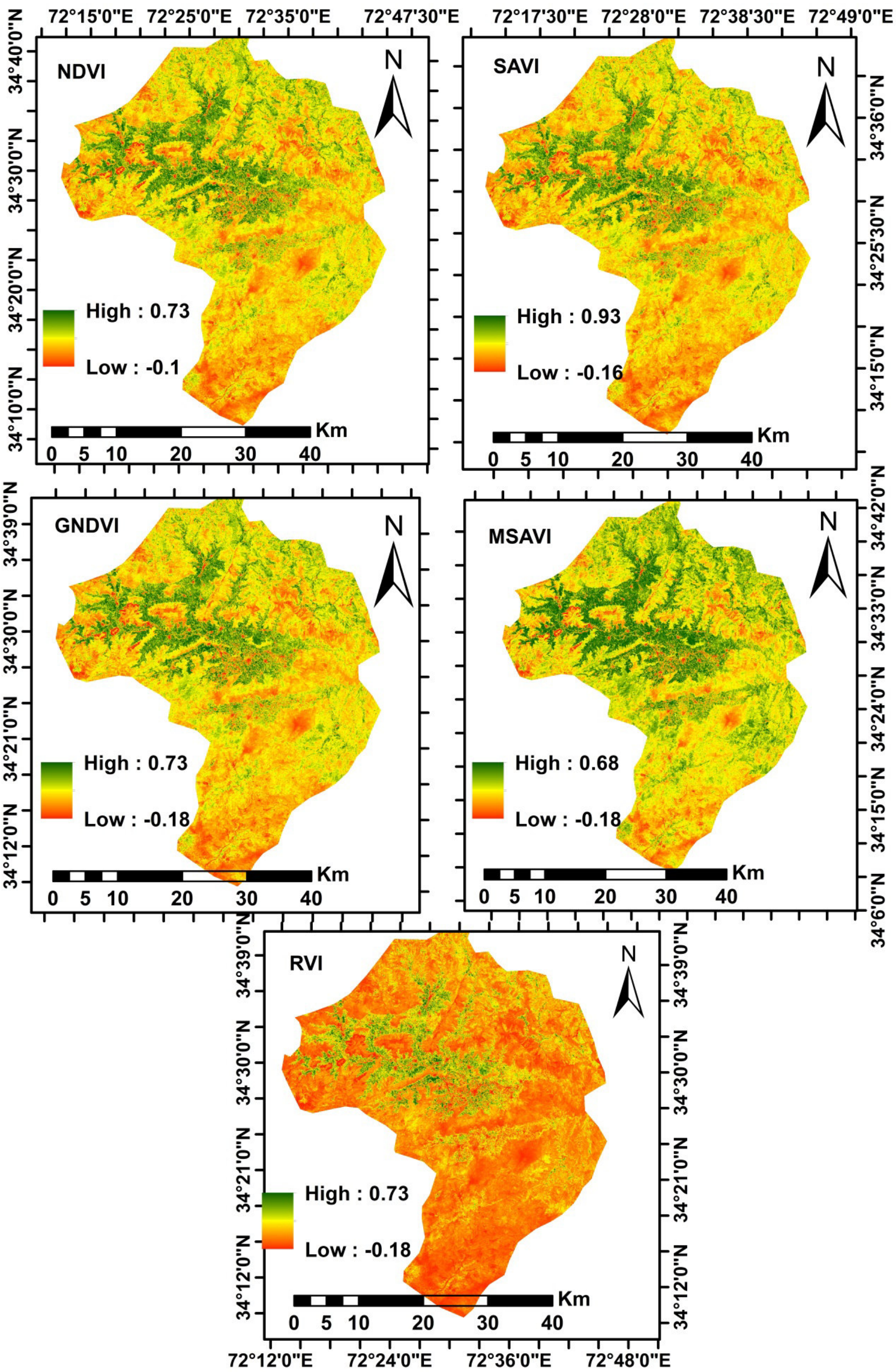

Fig. 2. *Spectral Indices of Landsat-8*

3.4. Correlation and Single Predictor Regression (SPR)

Vegetation indices computed from Landsat-8 images include NDVI, SAVI, MSAVI, DVI, and GNDVI (Figure 2). The correlation matrix shows that RVI had the highest correlation among the indices with R^2 value of 0.88 followed by NDVI, SAVI, and GDVI, with R^2 value of 0.83. MSAVI had the least correlation with volume. Regarding correlation between bands and volume, negative correlation was observed for all of the bands except Band 5. The highest correlation was observed for Band 7 with the R^2 value of -0.39 while the lowest correlation was shown by Band 1 (R^2 0.27) as depicted in Figure 3. Linear regression models were developed between vegetation indices and volume. The results from Figure 3 show that the best performance among the five indices was obtained by RVI with R^2 = 0.76, while the lowest performance was observed for MSAVI with R^2 = 0.66. Overall, all the indices performed well and showed that SPR explained more than 60% of the data variation. Barati et al. [7] compared various vegetation indices (NDVI, SAVI, MSAVI, GNDVI, TVI, DVI, etc.) and has found that the MLR model increased the R^2 values from 0.66 to 0.79. Lu [30] studied the impact of forest structure attributes in above ground biomass estimation using Landsat TM data and found that the MLR model was better than simple regression. Hese et al. [23] used multi-date field inventory and Landsat-5 data (TM and ETM) as well as techniques of change detection and artificial neutral network to map afforestation, reforestation, and deforestation.

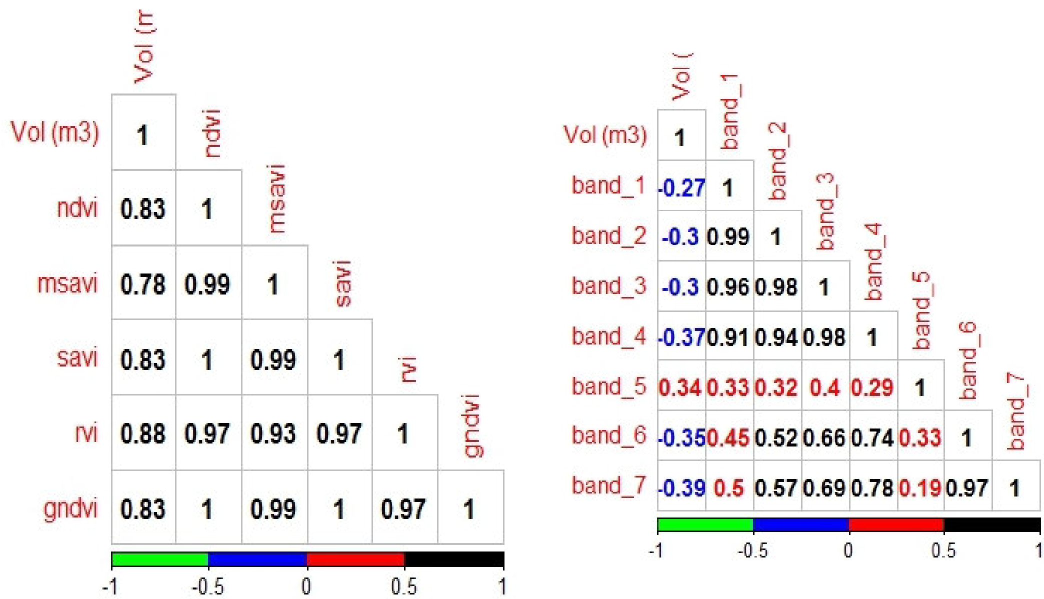

Fig. 3. *Correlation Matrix of Landsat-8 Spectral Indices and Bands with Volume [m^3]*

3.5. Stepwise Linear Regression (SLR)

The results summarized in Table 5 reveal that MASVI and SAVI were selected in stepwise linear regression as they had strong significant relationship with volume (p-value less 0.000), while the rest of the indices (NDVI, GNDVI, and RVI) were excluded (p-value greater than 0.05). The model summary showed that R^2 value (0.79) was a bit smaller than MLR R^2 (0.80), but a step-wise model has less predictor variables (2 variables). As compared to MLR, the SLR model is resistant to inter-correlation effects between model predictors.

Stepwise Linear Regression (SLR) – Indices versus Volume Table 5

Model Summary				ANOVA					
R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
.892	.796	.790	1.226	Regression	394.176	2	197.088	130.940	.000[d]
				Residual	100.847	67	1.505		
				Total	495.022	69			

Coefficients								
	Unstandardized Coefficients		Standardized Coefficients	t	Sig	Correlations		
	B	Std. Error	Beta			Zero-order	Partial	Part
(Constant)	.795	.846		.940	.351			
MSAVI	-58.723	8.968	-2.388	-6.548	.000	.752	-.625	-.361
SAVI	64.332	7.386	3.177	8.710	.000	.816	.729	.480

Excluded Variables		Model Equation
Index	Sig	a. Dependent Variable: Volume b. Predictors in the Model: (Constant), MSAVI, SAVI Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
Ndvi	.875	
Gndvi	.875	
Rvi	.351	

Regarding the SLR of bands and volume (Table 6), Band 7 and Band 5 were selected in stepwise method as their relationships were strongly significant with volume (p-value less 0.000) while the rest of the bands (Band 1, Band 2, Band 3, Band 4, and Band 6) were excluded (p-value greater than 0.05). The model summary shows that R^2 value increased from 0.418 to 0.436 as compared to MLR. Estornell et al. [18] developed stepwise regression analysis for biomass mapping using various variables such as spectral bands, NDVI, and height metrics derived from LiDAR data. The study found that using a combination of datasets with Lidar improved the accuracy (R^2 = 0.79) of biomass estimation. Model accuracy was assessed with Root Mean Square Error (RMSE) and it was found that the Simple linear regression model of RVI with volume (m^3) has the lowest RMSE (1.19), therefore considered best spectral index for mapping and monitoring plantations.

However, the stepwise model (MSAVI and SAVI) with RMSE 1.81 can be used for mapping (Table 7).

Stepwise Linear Regression (SLR) – Bands versus Volume Table 6

Model Summary[b]				ANOVA[b]					
R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
.661[b]	.436	.420	2.040	Regression	216.041	2	108.021	25.942	.000[b]
				Residual	278.981	67	4.164		
				Total	495.022	69			

Coefficients								
	Unstandardized Coefficients		Standardized Coefficients	t	Sig	Correlations		
	B	Std. Error	Beta			Zero-order	Partial	Part
(Constant)	-.481	1.699		-.283	.778			
band_7	-2.441	.414	-.546	-5.890	.000	-.481	-.584	-.540
band_5	5.802	1.175	.457	4.936	.000	.380	.516	.453

Excluded Variables		Model Equation
Index	Sig	a. Dependent Variable: Volume b. Predictors in the Model: (Constant), Band 5 & Band 7 Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
band_1	.186	
band_2	.179	
band_3	.098	
band_4	.229	
band_6	.069	

RMSE for Linear Regression Models Table 7

Model	Regression	RMSE
$\text{Volume} = 0.8553 \cdot \text{RVI}^2 - 0.8899 \cdot \text{RVI} + 0.446$	Simple Linear Regression	1.19
$\text{Volume} = -58.723 \cdot msavi + 64.332 \cdot \text{savi} + 0.795$	Stepwise Linear Regression	1.81
$Volume = 5.802 \cdot B_5 - 2.441 \cdot B_7 - 0.481$	Stepwise Linear Regression	2.20

3.6. Temporal Change-Afforestation

Temporal assessment of afforestation by Landsat-8 images showed that plantation was successful in the sampled sites. Figure 4 shows the values of RVI for the year 2013, 2016, and 2018. The RVI values increased over time due to seedlings or regeneration growth. Moreover, this is more clearly represented in Figure 5, which shows that forested areas have increased from 2013 to 2018. The RVI differencing and threshold measured area under vegetation was 7,309.7 ha in 2013 and was increased to 9,224.9 ha in 2018. WWF [47] also reported similar plantation areas in district Buner. Mancino et al. [32] used Landsat-TM images to assess the natural expansion of forests from 1984 to 2010. They computed NDVI and mapped vegetation changes over time by NDVI differencing and compared it with aerial photos. Similarly, Slimani et al. [42] adopted NDVI differencing and thresholding to highlight vegetation density and temporal changes while Barakat et al. [6] developed forest density classes based on NDVI thresholds and Google Earth Images. The classes were NDVI <0.1: without vegetation, 0.2 < NDVI < 0.4: slightly dense forest, 0.4 < NDVI < 0.74: dense forest.

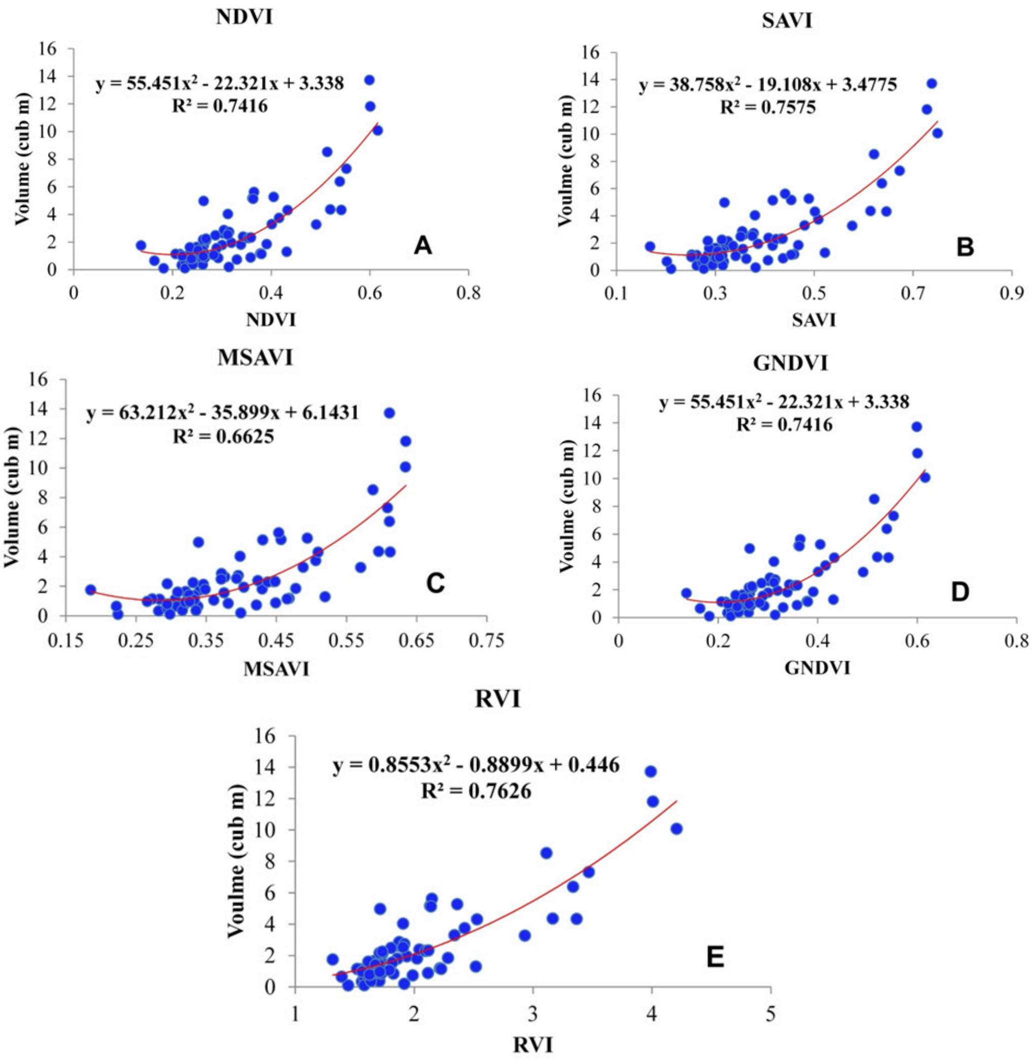

Fig. 4. *Scatterplots of Spectral indices and Volume [m^3]*

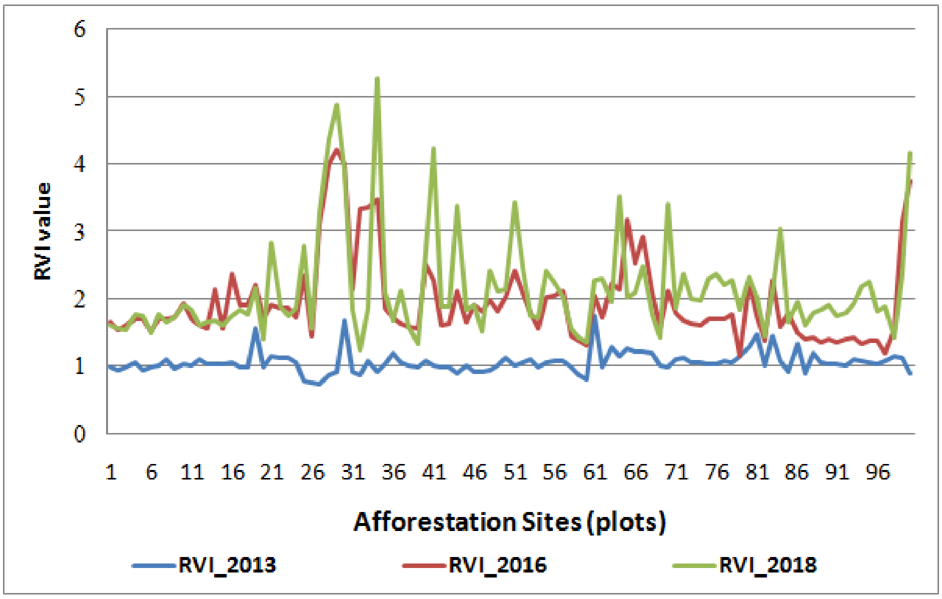

Fig. 5. *Temporal Change at plantation sites*

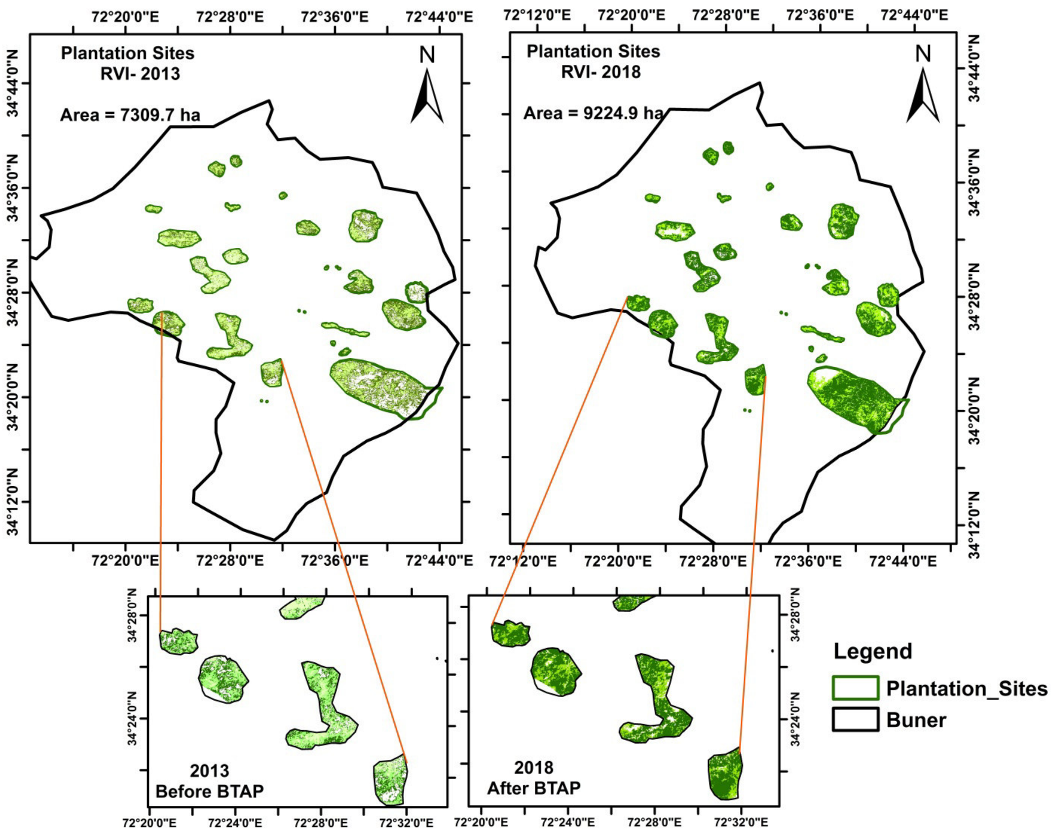

Fig. 6. *Plantation Activities of BTAP (Before and After)*

4. Conclusions

The study concluded that plantation activities were successful and have shown excellent survival rates and growth performance. The composition of natural regeneration was 70% sticky hop bush (*Dodonea viscosa* Jacq.), 24% of *Acacia* and some other species including Indian jujube (*Ziziphus mauritiana* Lam.), chir pine (*Pinus roxburghii* Sarg.), kamala tree *(Mallotus philippensis* (Lam.) Muell. Arg.) and black locust (*Robinia pseudoacacia* L.). The study indicates that the majority of the regeneration, i.e. 75% was established (above 9 inches) while only 25% was found unestablished (below 9 inches). The data revealed that the average survival rate was 93.75% which is comprised of the Daggar forest sub-division and Chamla forest range. In the Daggar Forest Sub-division the survival rate was 92.24% while in Chamla Forest Range it was 95.28%. Species composition was 83% river redgum (*Eucalyptus camaldulensis* Dehnh.), 14.21% chir pine (*Pinus roxburghii* Sarg.), 1.57% black locust (*Robinia pseudoacacia* L.) and 0.32% deodar (*Cedrus deodara* (Roxb.) G.Don). Out of five species that have been planted, river redgum (*Eucalyptus camaldulensis* Dehnh.) and chir pine (*Pinus roxbughii* Sarg.) were the major species in these plantations. While our results showed plantation success, but these efforts may largely be unsatisfactory in the long-run if issues like lack of local community participation, ineffective private-sector involvement, and regular monitoring, are not addressed [5]. River redgum (*Eucalyptus camaldulensis* Dehnh.) was planted in a high number which should be reduced and local indigenous species should be preferred for improving the biodiversity of the area.

This study used Landsat-8 temporal images from 2013 to 2018 to study the temporal response of vegetation indices. Further, the study provides growth performance, i.e., volume, and integrates the various spectral indices computed from Landsat-8 images. Open-source remote sensing products (Landsat-8) have a great potential in mapping and monitoring large-scale afforestation programs. Landsat-8 provides free multi-date satellite images to forest managers for long-term monitoring of forest cover. Landsat-8 spectral indices and band ratios provide enough information that can efficiently be used for Forest Landscape Restoration (FLR). However, use of other products such as Sentinel-2 can give better results because of its higher resolution. Further, higher accuracy can be obtained by combined use of optical datasets, active products (Sentinel-1 or SAR), and LiDAR. This integrated approach is challenging but possible with additional data and expert information. Thus, open-source products such as Landsat-8, Sentinel-2, and Sentinel-1 have great potential to map and monitor BTAP activities not only in Buner Forest Division, but also upscaled to regional or national level monitoring with acceptable accuracy. There is a need to repeat such studies in the future to assess and monitor the survival rate and growth performance of plantations established under BTAP. Due to shortage of time, this study could not cover all the sites where plantations were established. It is also recommended to investigate the impacts of BTAP plantations on ecological systems such as biodiversity, hydrological patterns, and carbon sequestration after 5-10 years to ascertain the impacts on the ecosystem.

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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