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Research Article

Assessment of *Taungya* agroforestry system in dryland forests rehabilitation in Sudan

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Abstract

The decline of the forest cover due to deforestation and agricultural expansion in Sudan has reached a critical situation. Taungya agroforestry systems have been used as a strategy to safeguard against this process, allowing farmers to cultivate their subsistence crops at the early stage of tree plantations. The current study research tackled Nabag Forest Reserve (NFR) as a case study to assess and explore *Taungya* agroforestry system as a practice used for forest rehabilitation in the study area. Satellite images of Landsat 5 Thematic Mapper, and Landsat 8 Operational Land Imager/Thermal Infrared Sensor of 1991, 2001, 2011, and 2021 were used to generate forest cover maps. Both unsupervised and supervised classification, as well as ground truth points, were applied to classify the vegetation cover in NFR as dense forest (DF), light forest (LF), agricultural field (AF), and bare land (BL). The results showed that two trends of forest cover changes occurred in NFR between 1991-2001 and 2011-2021. It was well explored that through *Taungya* agroforestry, there was a considerable increase in forest cover over this period. This could be clearly detected by increasing dense forest and light forest cover by 1041.73 ha (24.95%) and 2.95 ha (0.07%), respectively and decreasing of bare land and agricultural field by 409.79 ha (9.81%) and 634.52 ha (15.15%) during the addressed period. The findings of the study indicated that *Taungya* agroforestry system could be a feasible land-use alternative for forest recovery in the dry land of Sudan.

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Introduction

Forests contribute significantly to ecosystem services, climate change mitigation, and rural livelihoods improvement (Fekadu et al., 2021). International agreements and national policies recognize forest conservation, forest rehabilitation, and adaptation of sustainable forest management to climate change as critical for human livelihoods and climate stability (Buckingham et al., 2016). Despite the critical role forests play in sustaining ecosystem function and human needs, the pace of deforestation and forest degradation continues to rise (Keenan et al., 2015). However, forest cover has decreased dramatically during the last millennium, declining from approximately 6 billion ha to 4 billion ha (Agevi et al., 2016). According to the last Forest Resources Assessment (FRA) provided by the Food and

Agricultural Organization of the United Nations (FAO), approximately 420 million ha of the world's forests has been lost due to deforestation estimated at 10 million ha between 2015-2020. Africa experienced the largest annual net loss rate at 3.9 million ha (FAO, 2020). According to Abdon (2020), Sudan's vegetation cover area has decreased dramatically from 40% to 10.3%, with an annual removal rate of 1.6%. The main causes of deforestation and forest degradation include agricultural expansion (Hamunyela et al., 2020; Plata-Rocha et al., 2021) and forest over-exploitation (Jayathilake et al., 2021). In Sudan, for instance, most of the population in rural areas rely heavily on forests as a means of livelihood (Fahmi et al., 2018). Daur et al. (2016) argue that forest products supplement the primary source of income for rural livelihoods in most remote areas of Sudan. For instance, in the study region, the selling of Non-Timber Forest Products (NTFPs) represents a subsistence, food security and income strategy for rural households (Ibrahim et al., 2015). Another factor of land degradation could be attributed to mechanized rain-fed agriculture and shifting cultivation (Biro et al., 2013).

Forest rehabilitation and forest restoration concepts are frequently used interchangeably in the literature on interventions to recover the degraded forest (Jones et al., 2022). Forest rehabilitation encompasses a variety of practices that are planned, funded, implemented, and monitored by different actors such as governments, NGOs, and smallholders (de Jong, 2010). Ultimately, rehabilitation is needed to halt degradation, expand forest cover (Kobayashi, 2004) as well as generate various benefits for the adjacent communities, including ecosystem services (Nugroho et al., 2020) and livelihood improvement (Etongo et al., 2021). However, for the purpose of this study, the definition of CIFOR (2003), which defines forest rehabilitation as ‘‘Deliberate activities aimed at artificial and/or natural regeneration of trees on formerly forested grasslands, brushlands, scrublands or barren areas for the purpose of enhancing productivity, livelihood and/or environmental service benefits’’ was adapted. This definition was used because, in the case of Sudan, forest rehabilitation interventions target forested land that is exposed to different degrees of degradation.

Recently, there have been regional and global goals towards forest rehabilitation (Shahanim et al., 2022). As noted by UN Environment (2019), the aspiration is to reach 350 million hectares of forest restoration by 2030. In this regard, agroforestry systems ‘‘where woody perennials (trees, shrubs, palms, bamboos, etc.) are deliberately used on the same land management units as agricultural crops and/or animals, in some form of spatial arrangement or temporal sequence’’ (FAO, 2021), have been recommended as the most appropriate model and adequate solution for forest restoration and recovering degraded land (Miccolis et al., 2019). Budiastuti et al. (2021) noted that a sustainable agroforestry system was approved to be the best vegetation management to solve the problem of deforestation. Some experiences around the world, including Niger, Mississippi, and the Democratic People's Republic of Korea (DPRK) have a successful restoration program through agroforestry adoption. In Niger, farmers have restored 5 million hectares by planting more than 200 million trees through productive agroforestry practices (Buckingham and Hanson, 2015). In Lower Mississippi River Alluvial Valley (LMAV), agroforestry systems have been explored for restoring Bottomland Hardwood Forests (BLH) (Dosskey et al., 2012). Likewise, in DPRK, some agroforestry projects have been shown to be an effective tool for arresting deforestation and land degradation (Xu et al., 2012).

Taungya system is one of agroforestry systems, where annual crops are growing alongside forestry trees during the initial stages of forest plantation establishment (Azeez et al., 2017). The system was originally generated in Myanmar in the early 19th century (Acheampong et al., 2016) and has been widely used in some countries as an effective and inexpensive technology for the rehabilitation of the forest cover and livelihood improvement for farmers (Fatma et al., 2020). In Sudan, however, *Taungya* system is considered as one of the strategies implemented by the Forest National Cooperation (FNC) to halt deforestation and forest degradation. In the program, the FNC allocated a predetermined area inside the reserved forests and provided the farmers with tree seeds/seedlings and technical assistance. The farmers are responsible for planting specific crops allowed by FNC, such as sesame (*Sesamum indicum* L.), cowpea (*Vigna guiculata* L.), groundnut (*Arachis hypogaea*), and roselle (*Hibiscus sabdariffa* L.) (El Tahir et al., 2015).

Unlike in Ghana, Ethiopia, Kenya, and Nigeria where numerous studies have been published on the *Taungya* system (Azzez et al., 2017; Renner, 2017; Appiah et al., 2020; Nigussie et al., 2020), little is known about *Taungya* system for forest recovery in Sudan. Particularly in the dryland of Sudan, where the study area is located. Thus, to bridge this gap in the body of literature, such information is needed to inform decision-makers with empirical evidence about the potentiality of *Taungya* agroforestry system as a viable land-use practice for dryland forests rehabilitation. This could be the first step towards the formulation of future intervention in agroforestry projects that target forest cover rehabilitation. Therefore, the aim of the current study was to assess the potentiality of Taungya system as a land use practice in the rehabilitation of forest cover in dryland, South Kordofan State, Sudan.

Material and Methods

Study area

The study was conducted in South Kordofan State, Dilling district. Nabag Forest Reserve (NFR) was taken as a case study. It lies between the latitude 12°30'0" N to 12°36'0" N and the longitudes 29°36'0" E to 29°58'0" E (Figure 1). NFR was reserved in 1961 as a state forest and managed by FNC. It covers an area of 4174.2 hectares. The dominant tree species are *Acacia senegal*. The other natural tree species include *Azadirachta indica*, *Balanites aegyptiaca*, and *Sclerocarya birrea*. It is noteworthy that the study site has witnessed severe climatic extremes such as erratic rainfall, illegal felling, and continued land-use conflicts and there was visible degradation in the forest. Accordingly, the FNC introduced the *Taungya* agroforestry program for the rehabilitation of forest area. The program was started in 2005 and is still ongoing so far as a contract between the FNC and farmers, where the FNC is responsible for dividing the farmers inside the forest and providing them with the seedlings of *Acacia senagal* for planting, while the farmers plant their crops between tree spacing (Mohamedain et al., 2012).

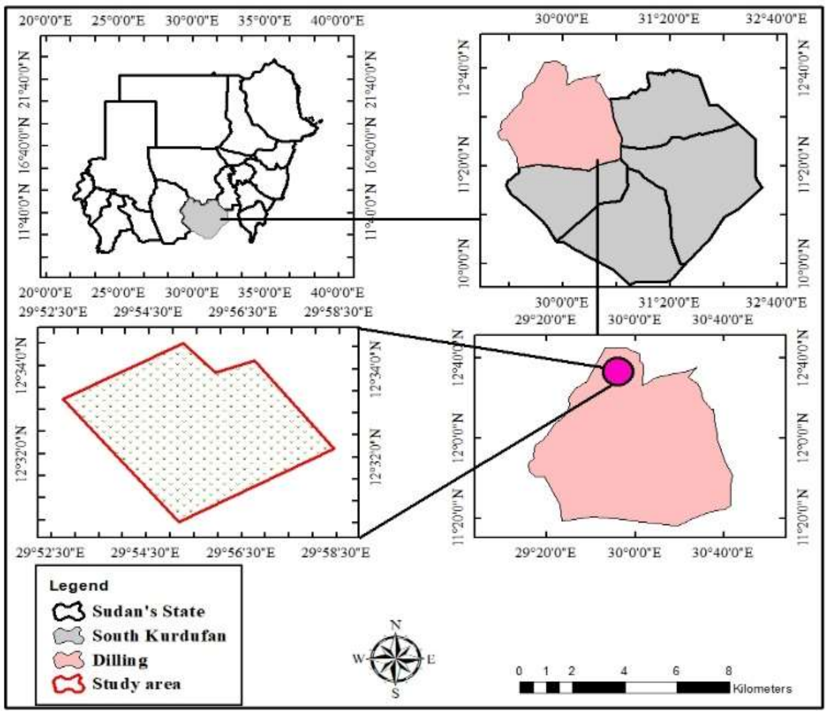

Figure 1. Map of the study area.

Data collection methods

The study used multiple approaches in collecting, processing, and analyzing the data. Includes remote sensing approach, ground-truthing survey, and field observations. Four satellite images of Landsat 5 Thematic Mapper (TM), and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) from the years 1991, 2001, 2011, and 2021 were selected respectively (Table 1). The selection of images was based on the availability of free cloud cover (>10%) satellites data. The images of 1991 and 2001 were used to detect the status of the forest cover before starting of *Taungya* agroforestry program, while images of 2011 and 2021 were used to detect the status after the program by applying a supervised image classification technique.

First, the coordinate of the study area was specified, and the boundary of the forest was delineated and reviewed in the Google Earth Pro Engine Platform. Afterward, the images of the study area were downloaded from the free website (USGS, earthexplorer.usgs.gov). Images of the study area were acquired during the dry season (January) for creating the training and classification. The dry period was suitable for getting free cloud cover satellite images to facilitate the differentiation between the different land cover classes.

Table 1. Source of satellite images used in this study.

Satellite name	Sensors	Resolution	Acquisition date	Path/Raw	Used band
Landsat 5	TM	30m	1991-01-20	175/051	B1- B7
Landsat 5	TM	30m	2001-01-15	175/051	B1- B7
Landsat 5	TM	30m	2011-01-11	175/051	B1- B7
Landsat 8	OLI/TRIS	30m	2021-01-06	175/051	B1- B7

Source: USGS, earthexplorer.usgs.gov 2021.

Second, image Preprocessing was performed on all acquired images by using geospatial analysis software (Open-source QGIS). All the bands of the four images scenes were downloaded and saved as separate image files (.tiff format). Then, the individual bands were combined sequentially from band 1 to band 7 using virtual raster creation. A false-color composite was performed for display Purposes. Lastly, a subset was generated from the virtual raster and clipped to get the full extent of the study area, which was used for creating the training dataset for image classification. The WGS 84 Projection Coordinate System was used to project all images to the Universal Transverse Mercator (UTM) Zone 35N.

Third, the ground truth survey was carried out during the summer season of 2021 to validate the land cover classes and for accurate assessment of the classification results. A random sample of 250 ground truth points was generated in QGIS software using a stratified random technique (Wanger and Stehman, 2015). Data was exported to the Google Earth Pro platform for visual interpretation (Figure S1). All sample points were entered into Global Positioning System (GPS) and used for the field survey validation.

Fourth, unsupervised and supervised classifications were employed to classify the images. The unsupervised classification was used to discriminate various land use categories in the study area and to avoid the mixed pixels between different classes. Then, supervised image classification was applied. At first, a set of training signatures were created for each predetermined land cover class by using polygon delineated (ROI). This was done based on the visual interpretation (false-color composite interpretation), prior knowledge of the study area, focus group discussion with forestry officials implementing the *Taungya* agroforestry program, and google earth time-series images. Accordingly, a total of four land types of classes were identified, namely, bare land (BL), agricultural field (AF), light forest (LF), and dense forest (DF). The characterization of these land types is presented in the appendices (Table S1 and Figure S2). Then, the maximum likelihood classifier (MLC) was run to obtain the final output of the classification.

Fifth, an accuracy assessment was performed for land cover maps by following an approach suggested by Congalton and Green (2019). User's Accuracy (UA), Producer's Accuracies (PA), Overall Accuracy (OA), and Kappa coefficients were determined, and then the error matrix of the land cover classification was produced by applying an approach used by (Berhanu et al., 2021).

Finally, the post-classification comparison method (PCC) was adopted to detect the forest cover change under *Taungya* agroforestry rehabilitation program. It is done by computing the magnitude and the percentages of change between different classes during the four years using the trajectory change matrix approach (Wu et al., 2015). Generally, all steps of the research methodologies approach used in this study are presented in (Figure 2).

Data analysis

Land cover changes were analyzed for different periods of satellite images between 1991-2001 and 2011-2021 using different geospatial analysis software. Percentage changes of land cover categories were calculated for the period times before and after the implementation of *Taungya* program in the study area.

Results and Discussion

Forest cover change detection

The results of land use land cover change maps of NFR during the period of 1991-2021 are illustrated in Figure 3, while the individual class area and related data are summarized in Table 2. The results of the temporal analysis of image classification showed that the total area of NFR was 4174.2 hectares (ha). NFR has witnessed two trends of forest cover change. First, a decline in forest cover occurred between 1991 and 2001. In 1991, the total area of the bare land class was 889.76 ha (21.3%) of the total area of NFR. It increased to 1004.85 ha (24%) in 2001. Similarly, the dense forest class faced a sharp reduction as the area radically declined from 582.05 ha (13.9%) to 322.2 ha (7.8%) (Table 1). This radical depletion of dense forests and the increment of bare land could be attributed to anthropogenic activities, severe climatic conditions, and a lack of forest management plans in this period. This assertion was supported by Abdel Magid and Mohamed (2015) and Mohamedain et al. (2012), who reported that NFR faced severe deforestation and degradation caused by the rural communities living surrounding the forest.

Similar studies carried out in the study region have demonstrated that reserved forests have witnessed a massive reduction in tree cover during this period due to anthropogenic and natural factors (Yasin et al., 2022). According to Elgubshawi et al. (2016), approximately 38% of the forested area was lost between 1986-2005, with an annual rate of 1.8%. The authors further argue that forest clearance increased two-fold between 1999-2005 (Elgubshawi et al., 2016). However, it is well established that the increment of the quantity of bare land and deforestation rate in forest areas have a detrimental effect on soil properties, hydrological regimes, and biodiversity enrichment (Sulieman, 2018; Veldkamp et al., 2020). This also was observed through the field survey where the regeneration of *Acacia senegal* seedlings was penurious in the bare land as compared to other classes. Conversely, the other two classes of agricultural field and light forest faced a slight increment of 1415.27 ha (33.9%) to 1440.54 ha (34.5%) and of 1287.02 ha (30.9%) to 1406.52 ha (33.7%), respectively.

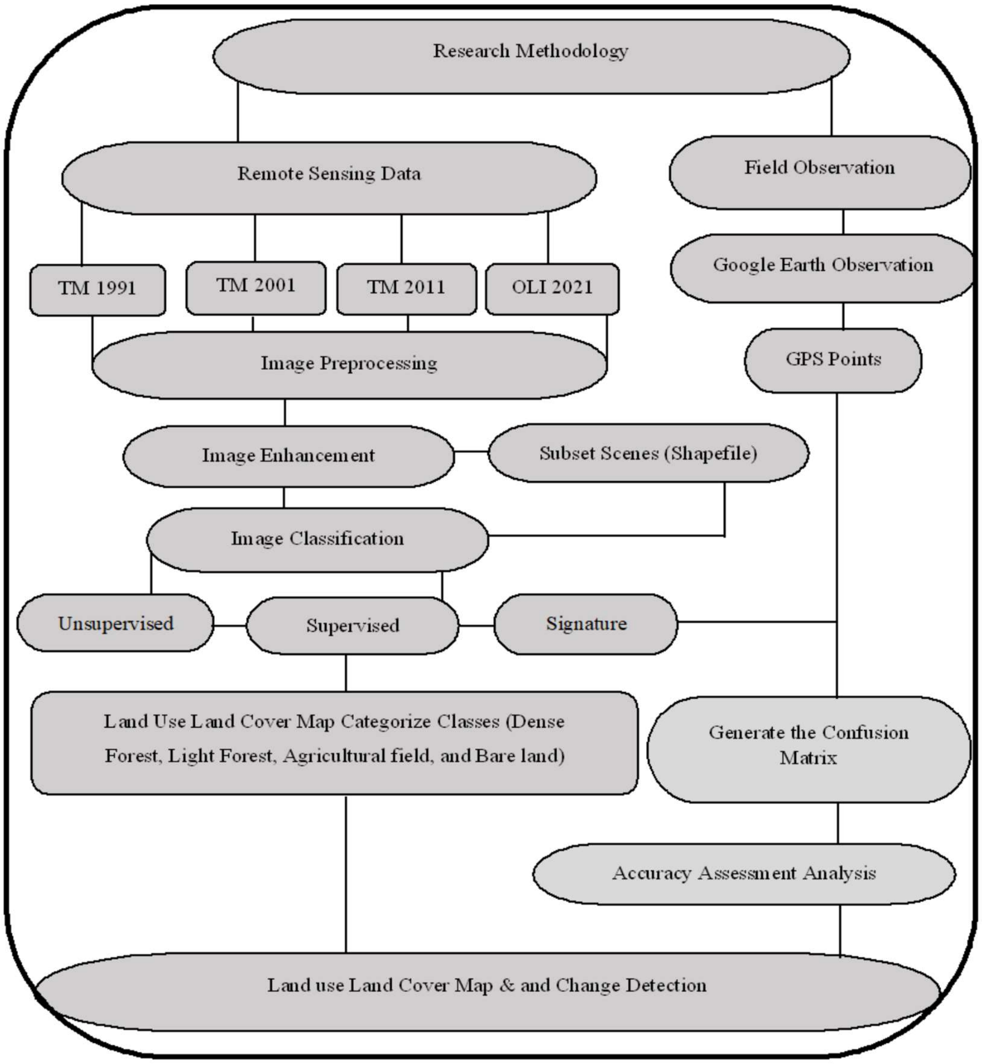

Figure 2. The methodological framework of the study.

Table 2. Areas and percentage of land use land cover changes in NFR between 1991-2021.

Class	1991		2001		2011		2021	
	Area/ha	%	Area/ha	%	Area/ha	%	Area/ha	%
BL	889.76	21.3	1004.85	24	809.64	19.4	479.97	11.5
AF	1415.27	33.9	1440.54	34.5	1550.79	37.2	780.75	18.7
LF	1287.02	30.9	1406.52	33.7	1435.86	34.4	1289.97	30.9
DF	582.05	13.9	322.2	7.8	377.82	9.0	1623.78	38.9
Total	4174.11	100	4174.11	100	4174.11	100	4174.2	100

Note: NFR= Nabag Forest Reserve; BL= Bare Land; AF= Agricultural Field; LF= Light Forest; DF= Dense Forest.
Source: classified images 1991, 2001, 2011, 2021.

Second, an increase in forest cover was observed in the period from 2011-2021. The major increment was detected in the dense forest class. Its share increased significantly from 377.82 ha (9%) in 2011 to 1623.78 ha (38.9%) in 2021. On the other hand, the bare land class declined gradually from 809.64 ha (19.4%) in 2011 to 479.97 ha (11.5%) in 2021. Studies done on forest rehabilitation show that planting trees can typically speed up forest vegetation recovery (Holl, 2013). Therefore, the increment in forest cover during this period could be explained by *Taungya* agroforestry program established by the FNC. According to the field visit and discussions held with the forestry officials working in the forest, the *Taungya* agroforestry program started at the beginning of 2005 to date. A study conducted by Salih (2013), reported a positive impact of the *Taungya* program in the rehabilitation of 3024 ha of NFR between 2005 and 2013. Another study conducted in Nigeria showed that *Taungya* system is beneficial for forest conservation and regeneration (Azeez et al., 2017). In contrast, the agricultural field and light forest, which were the dominant classes in 2011 with areas of 1550.79 ha (37.2%) and 1435.68 ha (34.4%) were decreased to 780.75 ha (18.7%) and 1289.97 (30%) respectively in 2021. It is noteworthy that other factors, such as environmental, political, and agricultural context, could also be responsible for these changes in the reserve during this period. These conditions play a critical role in land use and land cover changes (Hosonuma et al., 2012; Gadallah, 2018). As evidenced by reviewed literature, the history of the study region has witnessed a series of recurring dry years since 1982, as well as frequent civil wars that led to the loss of the vegetation cover (Deafalla et al., 2019).

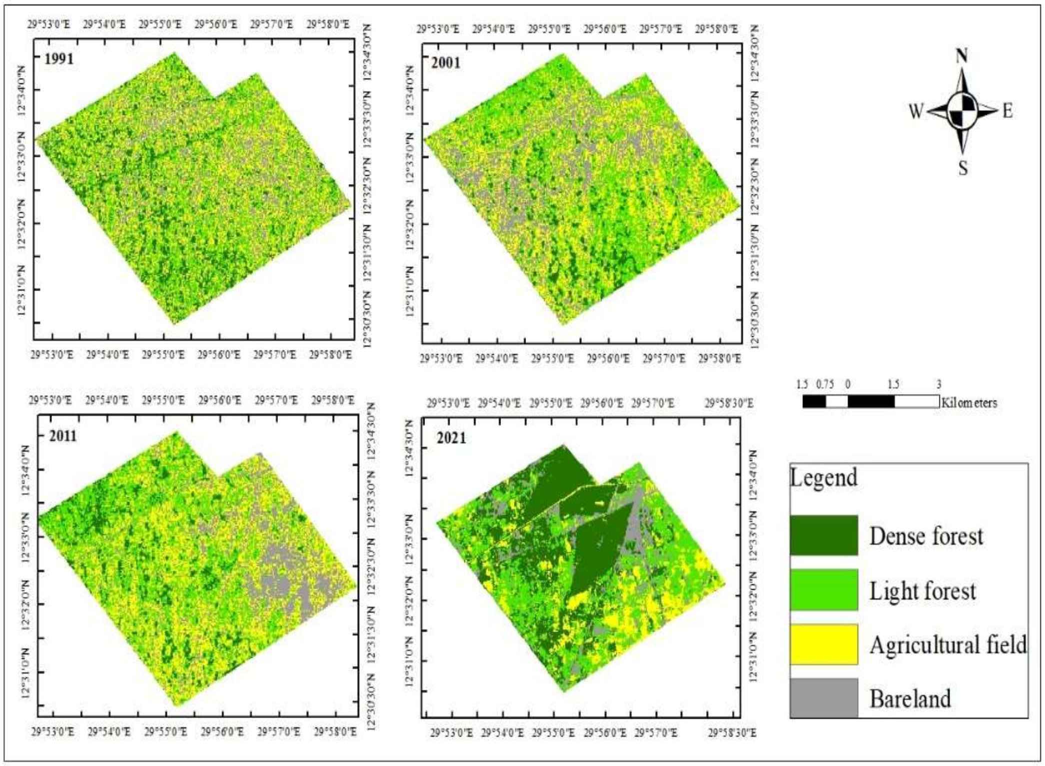

Figure 3. Maps of land cover change in NFR between 1991-2021.

Land use land cover change trajectories matrix

The land-use-land-cover change trajectory matrices of NFR during the periods 1991-2001, 2001-2011, 2011-2021, and 1991-2021 are shown in Table 3. Its maps are presented in Figure 4. The values depicted with bold letters illustrate areas and percentages of the unchanged classes, while the other values represent the magnitude of change from one class to the other for the given periods. Throughout 1991-2001, the total stability of the classes in the study area attained 1515.78 ha, while the major change was detected from agricultural fields to bare land. About 337.86 ha (38.1%) and 238.74 ha (26.9%) of agricultural fields and light forest, respectively, were converted to bare land, while a slight increase of 57.18 ha (9.8%) of bare land was changed to dense forest. Likewise, the dense forest class also declined as converted to light forest, agricultural field, and bare land accounted for 88.8 ha (6.3%), 35.34 ha (2.5%), and 10.41 ha (1.2%), respectively. This substantial change indicates the magnitude of deforestation and degradation that took place in the forest in this period. However, throughout 2001-2011, the dense forest and agricultural classes reached the highest stability with 158.94 ha (49.3%) and 581.76 ha (40.4%), respectively, although the lowest persistence was observed in bare land with 243.54 ha (24.2%). The reason for this is that during this period, the *Taungya* agroforestry program has already been launched by FNC in 2005, and accordingly, the bare land class witnessed the conversion to agricultural fields, light forests, and dense forests with 334.35 ha (23%), 219.87 ha (15.6%), and 11.97 ha (3.7%) respectively (Table 3). Between 2011 and 2021, the highest stability of land use classes was gained by dense forest and light forest, accounting for 179.37 ha (47.5%) and 392.85 ha (27.3%), respectively. Conversely, the bare land class declined to 40.4 ha (17.3%), whereas 91.98 ha (24.3%) of the agricultural field was converted to dense forest.

Table 2. Land use land cover change Trajectory matrices between 1991-2021 in NFR.

Class	BL		AF		LF		DF		Total/ha
	Area/ha	%	Area/ha	%	Area/ha	%	Area/ha	%	
1991-2001									
BL	**300.69**	**33.9**	377.31	26.7	269.67	20.9	57.18	9.8	1004.85
AF	337.86	38.1	**534.87**	**37.8**	453.33	35.2	114.48	19.6	1440.54
LF	238.74	26.9	467.79	33.1	**484.2**	**37.6**	215.79	37.0	1406.52
DF	10.41	1.2	35.34	2.5	80.88	6.3	**196.11**	**33.6**	332.74
Total/ha	887.7	100	1415.31	100	1288.08	100	583.56	100	4174.65
2001-2011									
BL	**243.54**	**24.2**	334.35	23.2	219.87	15.6	11.97	3.7	809.73
AF	429.66	42.8	**581.76**	**40.4**	496.8	35.3	42.57	13.2	1550.97
LF	309.42	30.8	468.54	32.5	**549.09**	**39.0**	108.72	33.7	1435.77
DF	22.23	2.2	55.89	3.9	140.76	10.0	**158.94**	**49.3**	377.82
Total/ha	1004.85	100	1440.54	100	1406.52	100	322.2	100	4174.11
2011-2021									
BL	**140.4**	**17.3**	185.31	11.9	127.98	8.9	26.28	7.0	479.97
AF	157.95	19.5	**283.95**	**18.3**	246.6	17.2	91.98	24.3	780.48
LF	306.27	37.9	510.66	33.0	**392.85**	**27.3**	80.19	21.2	1289.97
DF	205.02	25.3	570.87	36.8	668.43	46.6	**179.37**	**47.5**	1623.69
Total/ha	809.64	100	1550.79	100	1435.86	100	377.82	100	4174.11
1991-2021									
BL	**113.67**	**12.8**	167.31	11.8	141.84	11.0	57.15	9.8	479.97
AF	143.61	16.1	**242.01**	**17.1**	252.6	19.6	142.53	24.5	780.75
LF	273.54	30.8	546.78	32.3	**414.54**	**32.2**	145.11	24.9	1289.78
DF	358.85	40.3	549.03	38.8	478.2	37.2	**237.7**	**40.8**	1623.78
Total/ha	889.67	100	1415.13	100	1287.18	100	582.49	100	4174.47

Note: Bold values illustrate areas and percentages of the unchanged classes.

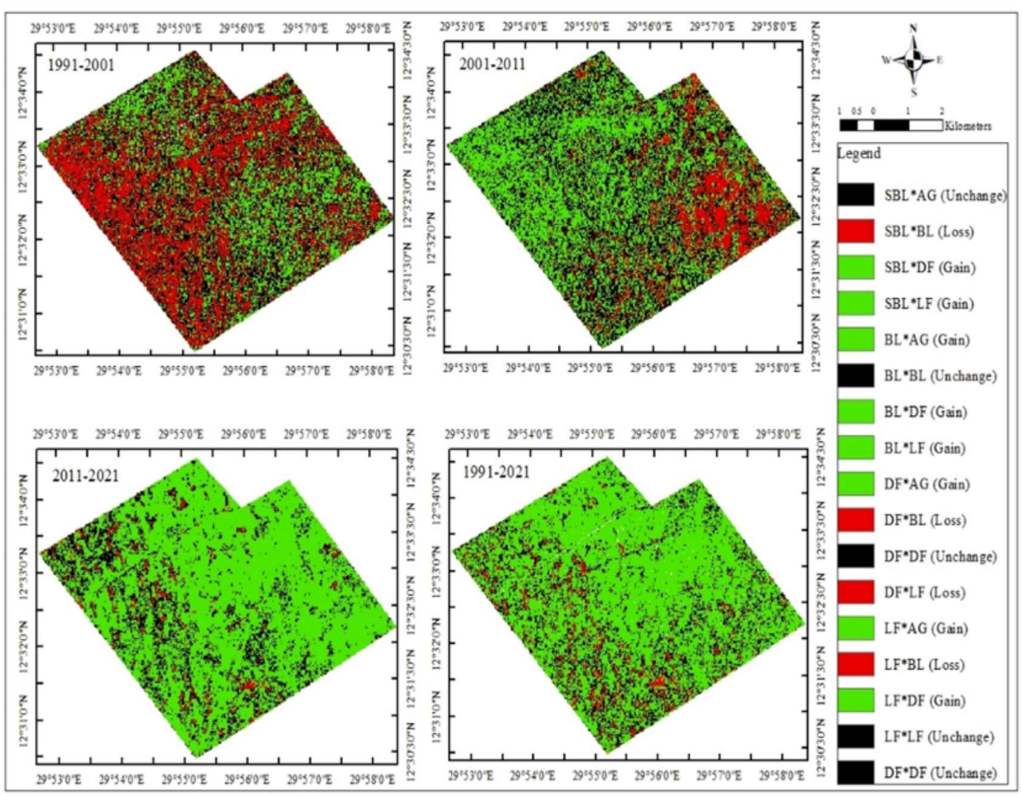

Figure 4. Trajectory matrix in NFR between 1991-2021.

Similarly, during the period between 1991-2021, the dense forest class was shown the highest persistence with 237.7 ha (40.8%) followed by light forest and agricultural field with 414.45 (32.2%) and 242.01 (17.1%) respectively, while the bare land class was less persistence with 113.67 ha (12.8%). This result affirms that during this period, the application and management of *Taungya* agroforestry succeeded in converting the bare land to forest cover, either in the shape of light forest or dense forest. This finding is in line with Eltayeb et al. (2013). The study reported that *Taungya* agroforestry was a successful approach to rehabilitate the bare land in El Rawashda forest reserve in the eastern part of Sudan. Elsewhere in Ghana, Taungya systems succeeded in rehabilitating about 250 ha of degraded forest areas (Blay et al., 2008). Generally, the trajectory matrix results (Table 3) revealed an increasing trend of forest cover both in dense forest and light forest classes followed by a substantial decline in bare land class during the study period.

Overall gain and loss of classes in NFR from 1991-2021

The overall gain and loss of different classes in NFR from 1991-2021 are indicated in Table 4. Results of this study showed that the dense forest was the major class in NFR, which shows a substantial gain of 1041.73 ha during the study period. Another slight gain was also detected in the light forest class with 2.95 ha. In contrast, Agricultural field, and bare land classes showed significant losses. The overall loss was found to be -634.52 ha and -409.79, respectively Figure 5. Although natural regeneration could be a reason for forest gain in the study area, the process is slow and it needs favorable conditions (Scheper et al., 2021), hence these gains and losses between different classes in the study area could be due to *Taungya* agroforestry rehabilitation program. Thus, the analysis of our results suggests that every bare land and area covered by agricultural field is likely to be converted to forest cover (dense forest or light forest) in the future.

Table 3. Overview of changes in different classes (ha) in NFR between 1991-2021.

Class	Net change (1991-2001)	Net change (2001-2011)	Net change (2011-2021)	Overall change (1991-2021)
BL	115.09	-195.21	-329.67	-409.79
AF	25.27	110.25	-770.04	-634.52
LF	119.5	29.34	-145.89	2.95
DF	-259.85	55.62	1245.96	1041.73

Source: classified images 1991, 2001, 2011, 2021.

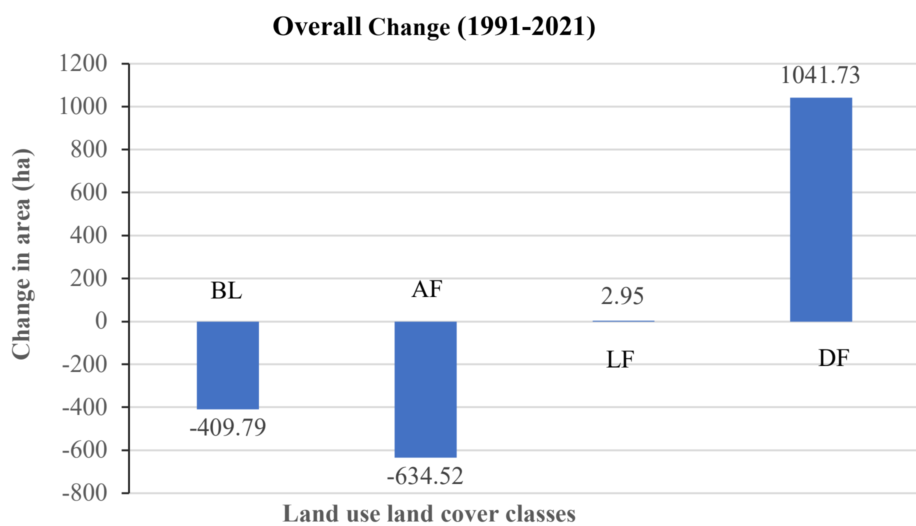

Figure 5. Graphical illustration of forest cover changes in NFR.

This has been observed during the study period from 2001-2011 and 2011-2021 respectively where the *Taungya* agroforestry program was launched. This reinforces the view of Gadallah et al. (2019) who noted that agroforestry practices could contribute significantly to recovering Sudan's forest cover if it involved in the forest management plans and strategies of the country. Observation similar to our findings was reported by Mishra et al. (2020) through their study of land use land cover change detection in India. In their study, traditional agroforestry systems were the main reason for increasing forest cover and decreasing the quantities of agricultural field and bare land area. This assertion was supported by Appiah et al. (2021) who analyzed the patterns of forest cover change in the Tano-Offin forest reserve in Ghana, their outcome concluded the possibility of agricultural land being converted to forest cover.

Accuracy assessment of classified images

The accuracy assessment confusion matrices of classified maps of 1991, 2001, 2011, and 2021 are illustrated in the appendices (Tables S2-S5), respectively. The overall accuracy of different classified maps was 80%, 83.2%, 80%, and 88.9%, and the associated Kappa's values were found to be 73%, 75%, 81%, and 82%, respectively. It is worth mentioning that these Kappa's values show acceptable classification.

Conclusion

This study explores the forest cover change under *Taungya* agroforestry program by taking NFR as a case study. The results showed that NFR had faced two different trends of changes over the study period. First, the reduction in forest cover classes (Dense Forest and Light Forest) was recorded in the period between 1991-2001, followed by a significant increase in bare land and agricultural field classes. Second, a substantial augmentation has been observed in the period between 2011-2021. However, within the study period of analysis (1991-2021), results indicated that forest cover classes increased from -259.85 ha to 1041.73 ha due to the establishment of *Taungya* agroforestry program. As a result, bare land and agricultural field areas decreased from 115.09 ha to -409.79 ha and from 25.27 ha to -634.52, respectively. Results recommended that every bare land covered by agricultural field is likely to be converted to forest cover in the future. Hence this study concludes that *Taungya* agroforestry could be a successful, suitable, and viable land-use option for forest rehabilitation in the dryland of Sudan. It is recommended that the FNC in Sudan should sustain the *Taungya* agroforestry program at NFR and imitate it in areas where forest rehabilitation is needed.

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Table S1. Definition of land use classes used in this study.

Land use classes	**Class description**
Bare Land (BL)	Areas no vegetation cover consisting of exposed soils
Agricultural Field (AF)	Areas covered by temporal crops followed by harvest period
Light Forest (LF)	Areas covered at least 10% and less than 40% of tree canopy
Dense Forest (DF)	Areas covered by more than 40% of tree canopy

Source: adapted from Sulieman (2018).

Table S2. Accuracy assessment of classified map of 1991.

Class	**BL**	**AF**	**LF**	**DF**	**Total**	**UA %**
BL	75	16	9	0	100	75
AF	13	80	7	0	100	80
LF	0	0	30	5	35	85.71
DF	0	0	0	15	15	100
Total	88	96	46	20	250	
PA % OA = 80% Cappa = 73.37%	85.23	83.33	65.22	75		

Note: From Table 6-9, PA= Producer Accuracy; UA= User Accuracy; OA= Overall Accuracy.
Source: classified image 1991.

Table S3. Accuracy assessment of classified map of 2001.

Class	BL	AF	LF	DF	Total	UA %
BL	81	10	9	0	100	81
AF	13	83	4	0	100	83
LF	0	0	29	6	35	82.86
DF	0	0	0	15	15	100
Total	94	93	42	21	250	
PA % OA = 83.2% Cappa = 75%	86.17	89.25	69.05	71.43		

Source: classified image 2001.

Table S4. Accuracy assessment of classified map of 2011.

Class	BL	AF	LF	DF	Total	UA %
BL	85	13	2	0	100	81
AF	5	89	6	0	100	83
LF	0	0	29	6	35	82.86
DF	0	0	0	15	15	100
Total	90	102	37	21	250	
PA % OA = 80% Cappa = 81%	94.44	87.25	78.38	71.43		

Source: classified image 2011.

Table S5. Accuracy assessment of classified map of 2021.

Class	BL	AF	LF	DF	Total	UA %
BL	47	7	1	3	58	81
AF	4	119	3	3	129	92.25
LF	1	1	26	1	29	89.66
DF	0	0	5	29	34	85.29
Total	52	127	35	36	250	
PA % OA = 88.4% Cappa = 82%	90.38	93.70	74.29	80.56		

Source: classified image 2021.

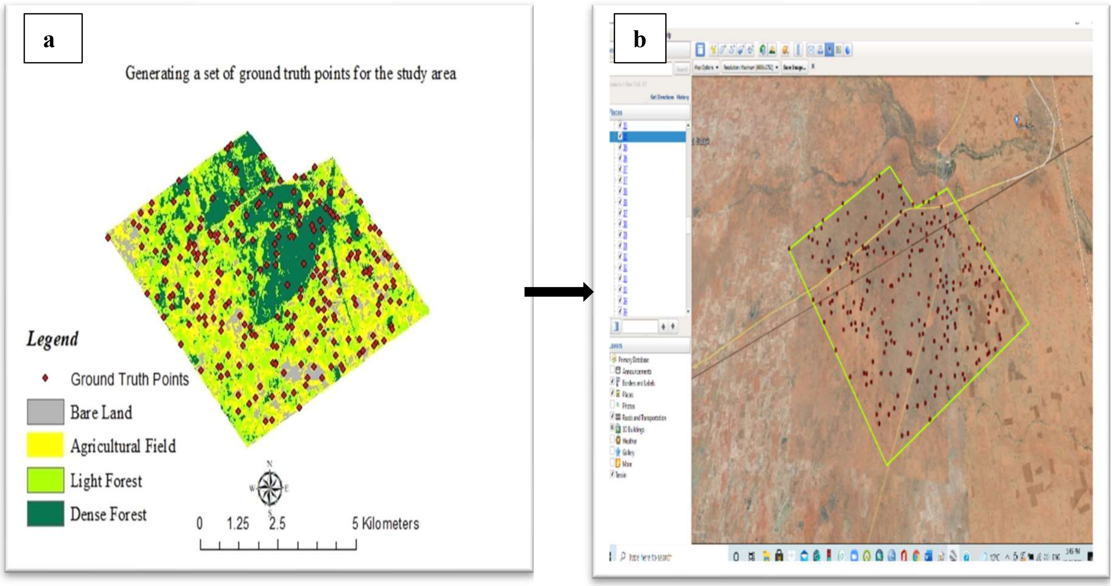

Figure S1. Generating ground truth points in QGIS (image a) and displaying the points in Google Earth Pro (image b).

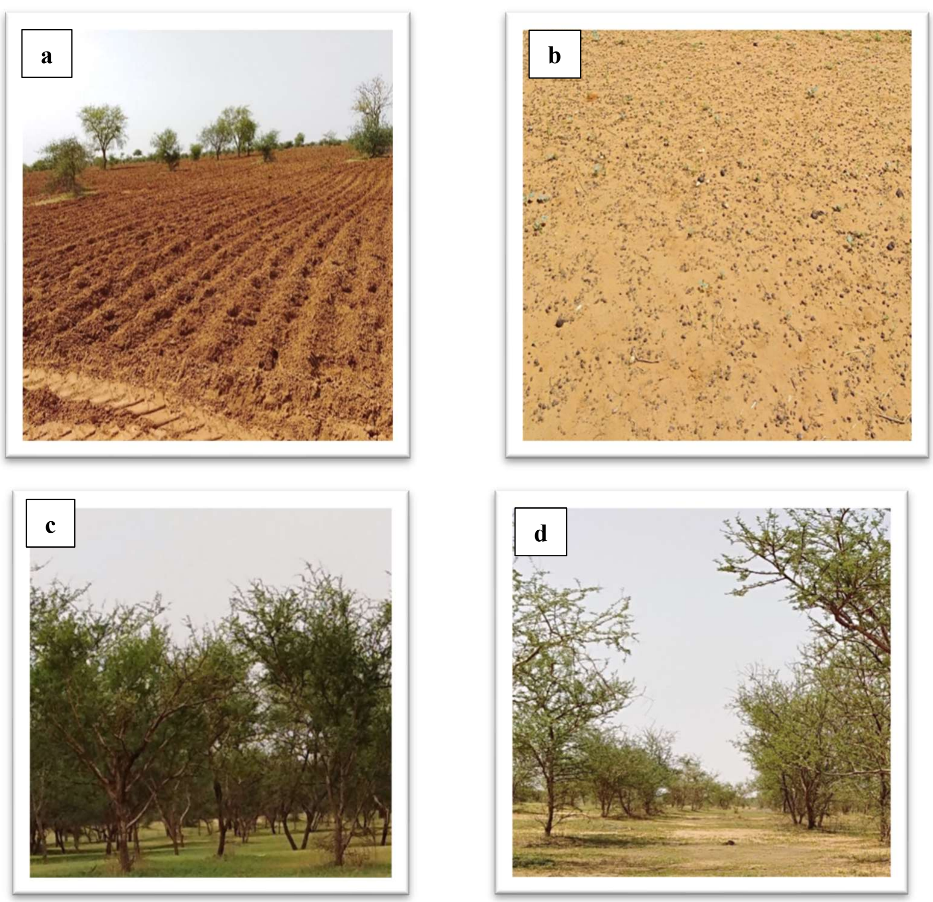

Figure S2. Illustrative photographs of different classes taken during the field survey in NFR. A= Agricultural Field; B= Bare Land; C= Dense Forest; D= Light Forest.