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Original Research Article

The impacts of armed conflict on vegetation cover degradation in Tigray, northern Ethiopia

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A B S T R A C T

Efforts made to restore the degraded landscape of the Tigray region, Northern Ethiopia, over the last three decades have been relatively successful. However, an armed conflict that broke out in the region in November 2020 has significantly destroyed the restored vegetation, either directly associated with conflict (environment, pollution, fire) or indirectly (agricultural abandonment). This study aimed at assessing spatio-temporal changes in vegetation cover in a 50 km radius zone centered on Mekelle city, Tigray. Vegetation cover dynamics was evaluated using Landsat Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI) datasets for the years 2000, 2020, and 2022 and analysed using ENVI 5.3 and ArcGIS 10.8.1 software. These data were analysed using the Modified Normalized Difference Vegetation Index (MNDVI), Optimized Soil Adjusted Vegetation Index (OSAVI), and Moisture Adjusted Vegetation Index (MAVI). Based on the MNDVI, results show that vegetation cover increased in the period 2000–2020 by 179 km^2 or 2% of the area, whereas in the period 2020–2022, there was a decrease in vegetation cover by 403 km^2 or 5% of the area. This was accompanied by a decrease in vegetation density. These vegetation changes in 2020–2022 are attributed to the impact of armed conflict on the land surface which can include farmlands and village abandonment, spread of weeds and scrub vegetation, or failure to harvest crops. Monitoring vegetation change using Landsat data can help understand the environmental impacts of armed conflict in rural agricultural landscapes, including potential food security risks.

1. Introduction

Efforts made by national stakeholders and local communities to restore the degraded landscape of Tigray in northern Ethiopia over the last three decades have had notable success. Various interventions in soil and water conservation practices, sustainable land management strategies, afforestation and re-afforestation programmes were implemented in the period 1991–2020 to restore degraded land in Tigray (e.g., Gebrehiwot et al., 2022; Gebremeskel et al., 2018; Noulèkoun et al., 2021). Research also shows how extreme land degradation in the Tigray region coupled with recurrent drought have been effective in offsetting a general trend of increased greenness and productivity than what existed some 145 years ago (Balehegn et al., 2019; Etefa et al., 2018; Nyssen et al., 2009a, b, 2014). Moreover, the watershed approach adopted in Tigray since the 1980s has helped restore degraded farmland, improve soil water holding capacities, increase woodlot cover, and improve the productivity of pasturelands (Gebremeskel et al., 2018;

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Tefera & Sterk, 2010). Since the 1990s, Tigray has also been undergoing landscape restoration focusing in management for soil conservation and land rehabilitation (Nyssen et al., 2009a, b, 2015) which has contributed to food security and the provision of other ecosystem services (Abera et al., 2020; Babulo et al., 2009; Weldetnsae MH, 2021). This refers to Tigray's conservation-based Agricultural Development-Led Industrialization (ADLI) strategy adopted in 1994 that was successful despite the increase in population of Tigray. This strategy caused reduced sheet and rill erosion rates, enhanced infiltration and spring water discharge, and higher values of vegetation through enhanced vegetation cover and crop production (Gebremedhin et al., 2003; Hagos et al., 1999; Kumasi & Asenso-okyere, 2011).

The implementation of the ADLI strategy in the Tigray region and its 20 days' voluntary free labor work deployment on soil and water conservation every year contributes much to restoration of degraded land. In addition, farmers who were entitled to the food/cash for work under the Productive Safety Net Programme were required to engage in conservation activities during the off-harvest period. This significantly enhanced vegetation restoration in the region. For example, Meaza et al. (2016) reported that vegetation cover in Tigray had increased due to improved forest management, implementation of soil and water conservation, and the plantation of native and exotic trees in previously degraded areas. The effectiveness of such community-based forest conservation strategies in Tigray was evaluated by Kidu et al. (2017). The ADLI strategy won the “Future Policy Gold Award in 2017” from the World Future Council because of its success in combatting desertification, improving soil fertility and resulting in greater crop productivity and food security (Hishe et al., 2017; Whiting, 2017).

Armed conflict is the act of war generated by two or more governmental groups, non-governmental groups, or international states that generally involves a combination of active military actions including aerial assault, naval craft operations, or ground forces that interact with the physical environment (Lawrence et al., 2015; Pearson, 2012). The impact of human conflict on the physical environment and its attributes are complex and multifaceted (Baumann & Kuemmerle, 2016; De Merode et al., 2007; Kiernan, 2015; Reuveny et al., 2010). Several studies have examined the impacts of warfare and armed conflicts on wildlife and ecosystem structure and function (Kanyamibwa, 1998; Lawrence et al., 2015; Ordway, 2015). A study by Aung (2021) in Rakhine, Myanmar, also revealed that the impacts of conflict were disastrous not only on human lives and properties, but also on the environment and ecosystems.

Armed conflict zones are difficult for researchers to conduct and collect *in situ* data for security reasons, the disruption of basic infrastructure such as telephone and internet facilities, and societal instability (Aung, 2021). Time-series assessment and monitoring of cultivated land as demonstrated by Weldegebriel et al. (2022), and vegetation cover in an armed conflict area, can be done using satellite imagery data and through a Geographical Information System (GIS). In Tigray, the time taken to restore degraded land and vegetation cover took three decades from the 1990s to 2020, while destruction of the restored areas has taken less than two years during the conflict. Tracking the recent degradation of vegetation due to conflict in Tigray can be evaluated using satellite imagery. Thus, the objectives of the study are to (i) assess the spatio-temporal conditions of the vegetation cover in the study area from different time slice in 2000, 2020, and 2022, and (ii) assess the impacts of war on vegetation resources and their management by rural communities.

2. Materials and methods

2.1. Description of the study area

The study area is located in Mekelle city and its surroundings in the Tigray region, northern Ethiopia. Mekelle has an estimated total population of 587,407 in 2023 with a growth rate of 4% (World Population Review, 2023). This population can also rapidly increase if internally-displaced people from outside the region are considered. From the center of the city, a radius of 50 km was taken to represent a zone of influence analysed in this study, making a total area of 7857 km^2 (Fig. 1). This broadly corresponds to the region within which farmers supply firewood and charcoal to the city. Moreover, these people are one of the most affected groups during the two years' armed conflict. Outside Mekelle city, the majority of rural residents are dependent on agriculture. Geologically, the study area is characterized by Basement complex, Paleozoic rocks, Cenozoic rock complex and Mesozoic sedimentary rocks (Kazmin, 1972). According to Ali et al. (2022), the study area is dominated by Luvisol, Calcisol, Verstisol, Fluvisol, Leptosol, Regosol and Cambisol soil types.

The two years of blockade and siege by the Ethiopian government in Tigray has created numerous crises of human welfare, the environment and biodiversity. After military operations in Tigray began in the early November 2020 (Abay et al., 2022), large-scale attacks took place in the region. Due to the presence of military activities, there was pressure on the environment to meet resource demands, including cutting trees for cooking and heating, and construction of military trenches in forest environments. During the military offensive, trees and natural vegetation were vulnerable to damage. Heavy shelling, drone and air attacks also significantly contributed to the destruction and burning of vegetated areas as well as limiting how local people could engage in agriculture and nature conservation activities in these areas. People were displaced from their homes and forced to settle in temporary refuge camps. The displaced people had no choice but to use felled trees for fuel (CEOBS, 2022; Plaut, 2021) as well as for sale. This is similar to the impacts of refugees displaced to the Democratic Republic of Congo from the 1994 Rwandan civil war, where more than 150 km^2 of forests were cut down for fuel by the refugees (Kanyamibwa, 1998). Existing community bylaws and grass-root level administrations in Tigray were weakened and institutions became non-functional during the conflict (Ghebreyohannes et al., 2022). Ethiopian and Eritrean forces, as well as the formal and informal military factions from the Amhara region, looted and destroyed crops, cattle, and farm equipment, as well as stockpiled grain from Tigrean farmers. (Nyssen et al., 2022; Weldemichel, 2021). The majority of farmers then experienced food insecurity in the subsequent months. Consequently, farmers were forced to cut previously-recovered vegetation in their locality and sometimes across the region in order to sell charcoal and firewood for additional income. Electricity blackouts in the cities resulted in a high demand of firewood and charcoal for cooking and light. This meant that every morning large numbers of donkeys and mules loaded with charcoal and firewood flooded into Mekelle, the capital city of the Tigray region, from different places mainly within a 50 km radius of the city. The farmers travelled at night in fear of checkpoints and for the illegal cutting of trees. On one hand, electricity supplies have been largely disrupted and are unreliable in the cities of Tigray, and on the other, the large-scale humanitarian crisis in rural areas that led to acute food shortages meant that rural communities were forced to collect and sell firewood and charcoal to sustain their livelihoods. Farmers

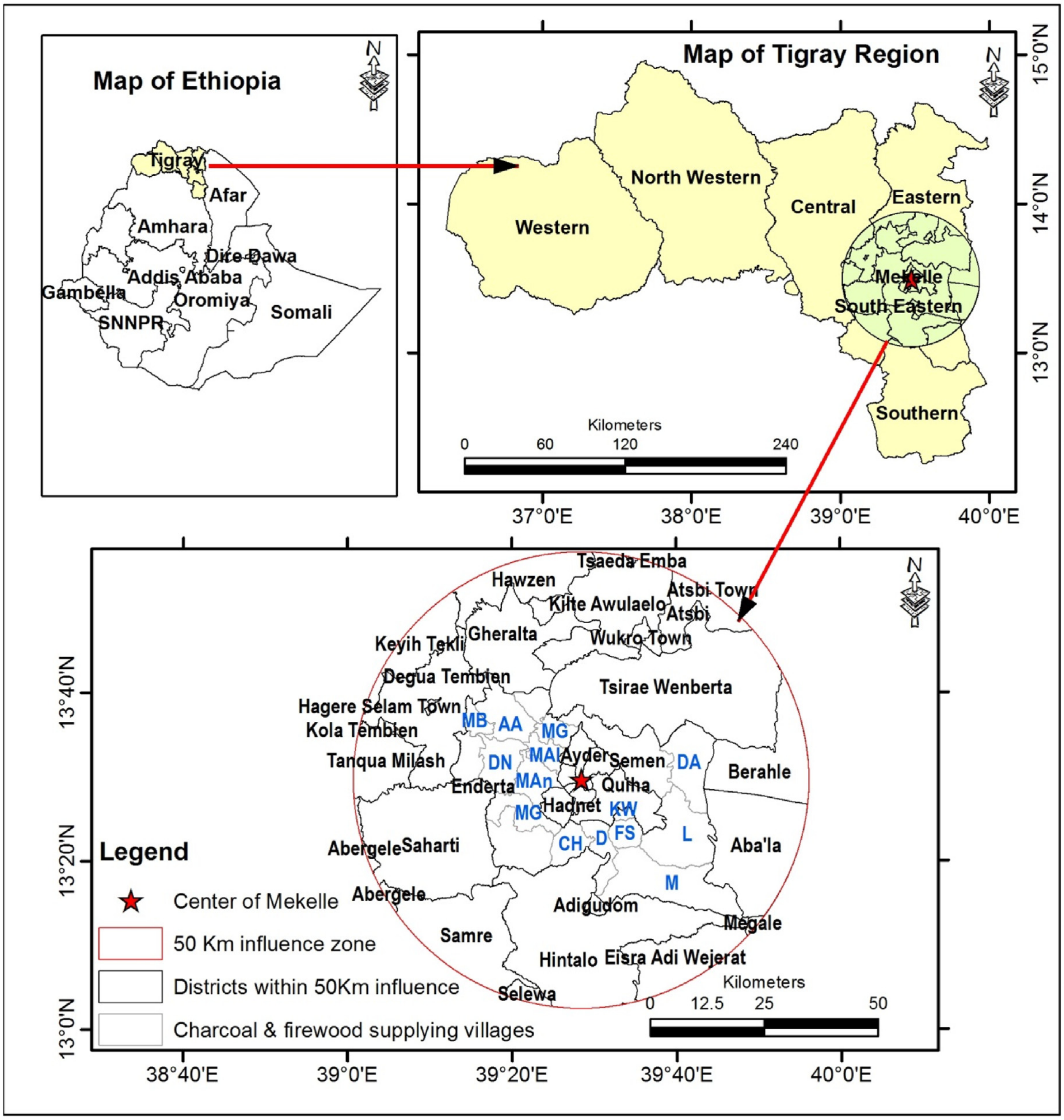

Fig. 1. Geographical location of the study area within a 50 km influence zone outwards from Mekelle city. Farmers supply charcoal and firewood to the city from the following villages: *DN = Debere Nazret, MB = Mizane Birhan, L = Lemelem, DA = Derga'ajen, AA = Adi Azmera, M = Meseret, MAl = Mai Alem, MAn = Mai Anbesa, KW = Kedamay Weyane, MG = Mai Genet, FS = Felege Selam, D = Didiba, MG = Mahbere Genet, CH = Chelekot.*

were mainly dependent on agriculture and livestock production which, at a local level, was relatively resilient through the conflict period (Ghebreyohannes et al., 2022; Nyssen et al., 2021).

2.2. Data collection and processing

Multi-resolution and multispectral Landsat imagery for the years 2000, 2020, and 2022 were used to analyze the spatio-temporal patterns of vegetation cover in the study area using different vegetation indices. The latest image was used to map changes in tree distribution due to land degradation and uncontrolled deforestation during the Tigray conflict. The downloaded images of different years were pre-processed using ENVI v.5.3 for geometric, radiometric and atmospheric corrections. For the Landsat ETM + images in 2000, bands 4, 3, 2 were used and for Landsat 8 OLI/TIRS images for 2020 and 2022, bands 5, 4, 3 were used to visualize in a false color composite and to better understand vegetation distributions. The Fast Line-of-sight Atmospheric Analysis of Hypercube (FLAASH) module in ENVI v.5.3 was used for atmospheric and radiometric correction (Hishe et al., 2019). After pre-processing and computing of each vegetation index, we mosaicked the three scenes and clipped by the study area. In order to integrate the 50 km radius of the study area with the Landsat images, we set a Universal Transverse Mercator (UTM) WGS 84 zone 37 N projections in ArcGIS v.10.8.1. The spatial resolution of each bands used in the computation was 30 m.

Informal and continuous communication conversations at different locations (Aynalem (13.47°N, 39.48°E); Mai-Alem (13.54°N, 39.42°E); and Sirawat (13.50°N, 39.44°E)) were held with local people who supply charcoal and firewood to Mekelle city. Moreover, discussions were also held with the Enderta district administrator on the past and current conditions of vegetation in the district. Personal observations and review of published and unpublished documents, and photographs were also data sources that were used to strengthen the study.

2.3. Indices for monitoring vegetation change

For better understanding of the Earth's surface, using and analyzing multispectral satellite data are efficient in detecting spatial and temporal changes of phenomena such as vegetation, and land use/land cover classification. Three different vegetation indices were used in this study. These are the Modified Normalized Difference Vegetation Index (MNDVI) developed by Nemani et al. (1993); the Optimized Soil Adjusted Vegetation Index (OSAVI) developed by Rondeaux et al. (1996); and the Moisture Adjusted Vegetation Index (MAVI) developed by Zhu et al. (2014). The equations for these indices, respectively, are:

$$\text{MNDVI} = \text{NDVI} \times (\text{SWIR}_{max} - \text{SWIR})/(\text{SWIR}_{max} - \text{SWIR}_{min}) \quad (1)$$

$$\text{MAVI} = (\text{NIR} - \text{R})/(\text{NIR} + \text{R} + \text{SWIR}) \quad (2)$$

$$\text{OSAVI} = (\text{NIR} - \text{RED}) \,/\, (\text{NIR} + \text{RED} + \text{Y}) \quad (3)$$

The justification for using these three different indices is as follows. The three band vegetation index (Red, near-Infrared (NIR), and Short Wave Infra-Red (SWIR)) used in a MAVI band ratio form reduces the topographic influence which cannot be achieved through the other indices (Zhu et al., 2014). The OSAVI uses the Red and NIR wavebands but also takes into account the standard value of 0.16 for the canopy background adjustment factor of variable Y in Eq. (3). This index is important to monitor areas with low-density vegetation or where bare soil is imaged through the canopy.

For spatial analysis undertaken in ArcGIS, random sample points were generated inside the district polygons at a distance of 1 km by specifying 10 points in each polygon. Therefore, 218 random points in total were generated for the entire study area. The vegetation index pixel values were extracted for MNDVI, OSAVI, and MAVI. Before the start of conflict in 2020, climatic data from *in situ* rain gauge records were used in Tigray. However, after the breakout of the conflict, government institutions become non-functional and climate data were not recorded. Thus, a precipitation dataset with a horizontal spatial resolution of 0.05° was retrieved from Climate Hazards Group InfraRed Precipitation (CHIRPS) dataset, available at https://www.chc.ucsb.edu/data/chirps. In order to regress with the vegetation indices, the precipitation data was first resampled into 30 m pixel resolution to conform with the Landsat data. The annual average precipitation pixel values of the random sample points were then extracted for 1999, 2019 and 2021. In order to account for the potential cumulative impact on plant health, the mean monthly precipitation (MMP) from the preceding year of the vegetation index periods was carefully taken into account. Finally, the precipitation data were regressed with the MAVI, OSAVI and MAVI models for the years 2000, 2020, and 2022. Albarakat & Lakshm (2019) and Stellmes et al. (2010) reported that, for determining any increase and/or decrease in vegetation cover, linear regression analysis is considered as the most effective approach. Therefore, simple linear regression was carried out for the MNDVI, OSAVI, and MAVI to observe any relationship between vegetation indices and precipitation. The linear trend model was quantified using the p-value statistical significance at confidence levels of 95% ($p < 0.05$) and the correlation coefficient (r).

3. Results

3.1. Changes to Modified Normalized Difference Vegetation Index (MNDVI)

The values of MNDVI range from −1 to 1, where values above 0 represent the presence of healthy vegetation. The study area is characterized as a semiarid environment dominated by sparse vegetation cover. Accordingly, we have used our own classification thresholds from low (0.1–0.2); medium (0.2–0.3); high (0.3–0.4) and very high (>0.4) values of MNDVI to be consistent with the other vegetation index classification used in this study. A study by Sahebjalal & Dashtekian (2013) also used similar classification threshold for NDVI density classes in the southern part of Ardakan, Iran. Table 2 shows the trends of vegetation cover in km^2 for the years 2000, 2020 and 2022. The year 2000 was in the pre-conflict period and 2020 was the start of the conflict. The year 2022 was expected to show a decline in vegetation cover as impacted by the conflict, and this is what is seen in Table 2. The CEOBS report (2022) identified hotspot areas of vegetation decline across Tigray that were most likely linked to the conflict, reflecting the increased need for fuel at this time. In order to consider in a more detail the changing vegetation cover in the study area, the density classes for different time periods were also examined (Table 2).

The highest coverage of vegetation in the pre-conflict era was observed in the low (0.1–0.2) density class. The increased cover between 2000 and 2020 in this low density class is considered to be the effects of conservation practices, implementation of community bylaws for protection of vegetation areas, and high awareness of community members on land management policy issues (e.g. Abera et al., 2020; Gebremeskel et al., 2018; Oniki et al., 2020). On the contrary, during the conflict in 2020–22, there was a significant decline in vegetation cover of all cases (Fig. 2(c)). Compared to the pre-conflict era, the average rate of change in the period 2020–22 was 20-times higher for low density vegetation classes, and two-to five-times higher for the medium and high/very high vegetation classes.

3.2. Changes to Optimized Soil Adjusted Vegetation Index (OSAVI)

The OSAVI is a vegetation index with the family of SAVI that minimizes the soil effects. For a place such as Tigray with sparse vegetation cover and the influence of bare soil on spectral signatures, the OSAVI is a better estimator of vegetation cover. In comparison with NDVI, the OSAVI-derived vegetation index is a more appropriate estimator for biomass and vegetation coverage in semi-arid regions (Fern et al., 2018). The value of OSAVI ranges between −1 and 1. In this study, similar to the other indices, OSAVI values above 0 was considered and classified into low (0.1–0.2); medium (0.2–0.3); high (0.3–0.4) and very high (>0.4) values (Table 3).

The trends of vegetation cover condition using OSAVI are very similar to MAVI, showing an increase in 2000–20 and decline in 2020–22. The lowest (0.1–0.2) density class is most dominant in the study area. However, it is notable that this class is significant greater in area than MNDVI, indicating the sensivity of OSAVI to soil and other environmental condition. The same broad temporal trends as MNDVI are also identified in OSAVI but with a greater magnitude of change in this lowest density class. The average rate of change in the period 2000–20 based on OSAVI data is broadly similar to results from MNDVI. Calculation of the average rate of change for the period 2020–22 shows that there was a high net loss of vegetation cover (of 1039 km^2 or 13% of the study area), associated with clearance for firewood and charcoal. Considering an OSAVI value of ≥0.1 as refering to healthy vegetation, the density of

Table 1
Characteristics of Landsat products with 30 m resolution acquired in the dry season used for analysis of different vegetation indices.

Data Type	Sensor Type	Path/Row	Acquisition date
Landsat 7	Enhanced Thematic Mapper Plus (ETM^+)	168/51	Feb 02, 2000
		169/50	Jan 19, 2000
		169/51	Feb 04, 2000
Landsat 8	Operational Land Imager (OLI)	168/51	Jan 19, 2020
		169/50	Jan 26, 2020
		169/51	Jan 26, 2020
Landsat 8	Operational Land Imager (OLI)	168/51	Jan 24, 2022
		169/50	Jan 31, 2022
Landsat 9	Operational Land Imager (OLI)	169/51	Jan 23, 2022

Table 2
Vegetation density classes based on MNDVI and their changes in different years.

MNDVI density classes	Area in km^2 and (% of total area examined in this study)			Change in km^2 and (% of total examined in this study)		Average rate of change in km^2/year	
	2000	2020	2022	2000–2020	2020–2022	2000 –2020	2020 –2022
Low (0.1–0.2)	1420.0 (18.08%)	1625.95 (20.70%)	1210.44 (15.41%)	+205.95 (+2.62%)	−415.51 (−5.29%)	+10.29	−207.75
Medium (0.2–0.3)	65.90 (0.84%)	42.70 (0.54%)	54.4 (0.69%)	−23.20 (−0.29%)	+11.70 (0.15%)	−1.16	+5.85
High (0.3–0.4)	3.91 (0.05%)	0.85 (0.01%)	1.57 (0.02%)	−.3.06 (−0.04%)	+0.72 (<0.01%)	−0.15	+0.36
Very high (> 0.4)	0.43 (<0.01%)	0.00 (0%)	0.17 (<0.01%)	−0.43 (<−0.01%)	+0.17 (<0.01%)	−0.02	+0.09
Total of vegetation covered area in km^2 (% of total mapped area)	1490.24 (18.97%)	1669.50 (21.25%)	1266.58 (16.12%)	+179.26 (+2.28%)	−402.92 (−5.13%)	+8.96	−201.45

vegetation cover substantially increased in the period 2000–20 (Fig. 3(b)), whereas following two years of war until 2022, there was a significant deterioration of low-density vegetation density (Fig. 3(c)).

We also considered pixel-by-pixel changes in OSAVI in the periods 2000–20 and 2020–22. As depicted in Fig. 4(a), results indicate that 23% of the study area had an OSAVI value less than zero, whereas 77% of the area had a value greater than zero (green shaded). This suggests that vegetation has been re-greening in this 20-year period. On the other hand, a change map for the OSAVI was computed for the conflict period (2020–22). This shows that the vegetated (OSAVI>0) and non-vegetated (OSAVI<0) land have equal area coverage (50%). This highlights the declining trend in vegetation cover at this time (Fig. 4(b)).

The ΔOSAVI in the period 2020–22 with no change was 49.50% of the total area, and areas with a vegetation cover decrease of 0–10% was 50.49%. The remaining 0.01% was shared in the other classes (Fig. 4(c)).

3.3. Changes to Moisture Adjusted Vegetation Index (MAVI)

Unlike OSAVI which includes the Red and NIR wavebands, MAVI considers the SWIR band. As such, MAVI can potentially be a better estimator of vegetation cover as it reduces the role of topographic effects on the vegetation index (Zhu et al., 2014). MAVI results are presented according to the low (0.1–0.2), medium (0.2–0.3), high (0.3–0.4) and very high (>0.4) density classes (Table 4).

The MAVI results show there was an increase of vegetation cover in the period 2000–20 by about one third for the low density class (0.1–0.2) although there was a slight decrease in other classes. By contrast, in the period 2020–22, the low density MAVI class showed a significant decline with minor changes experienced in the other classes (Fig. 5(c)). From the spatial analysis of MAVI data, areas of increased vegetation density for the period 2000–20 and a decrease for the period 2020–22 can be identified (Table 4, Fig. 5). Increased vegetation cover was dominantly observed east and west of Mekelle city.

The ΔMAVI in the period 2020–22 with no change was 41% of the total study area, and areas that show a decrease of 0–10% was 58% of the study area. The remaining 1% represents areas with an increase of 0–10%.

3.4. Vegetation degradation and strategies for remediation and restoration

Informal discussions with farmers who were selling firewood and charcoal in Mekelle city showed they came from a distance of 10–20 km from Shibta, Ashegoda, Hawsewa, Shafat, and Dagya sub villages to the east of the city. They mainly sell at the marketplace locally called kebelle 17 or Indaslassie market place. Suppliers from Dandera and Irgi Hariba villages sell firewood and charcoal at Quiha marketplace in Mekelle. However, the Enderta district administration is trying to confiscate the illegal supply of charcoal and firewood products, as indicated in Fig. 6(c). From the west of Mekelle city, farmers from Adi Azmera, Debre Nazret, May Anbesa, and Mai Genet villages are the most dominant and mainly supply firewood and charcoal on religious days. They sell their products at the temporary marketplace near to St. Gebriel church in the Hawelti area of Mekelle. Because of high demand of firewod and charcoal from *Acacia* trees, smallholder farmers mainly supply products from these trees (Fig. 6(b)). Furthermore, many farmers also walk door-to-door on the road with their loaded donkeys selling the charoal and firewood.

Informal discussion with the Enderta district administrator showed that before 2014 there was widespread deforestation in the district for the supply of firewood and charcoal. Farmers were traveling through the night with wood products to Mekelle city. In understanding these impacts of deforestation, an agreement was made with village administrations, religious leaders, youths, and older people to halt cutting trees in their communities. According to the

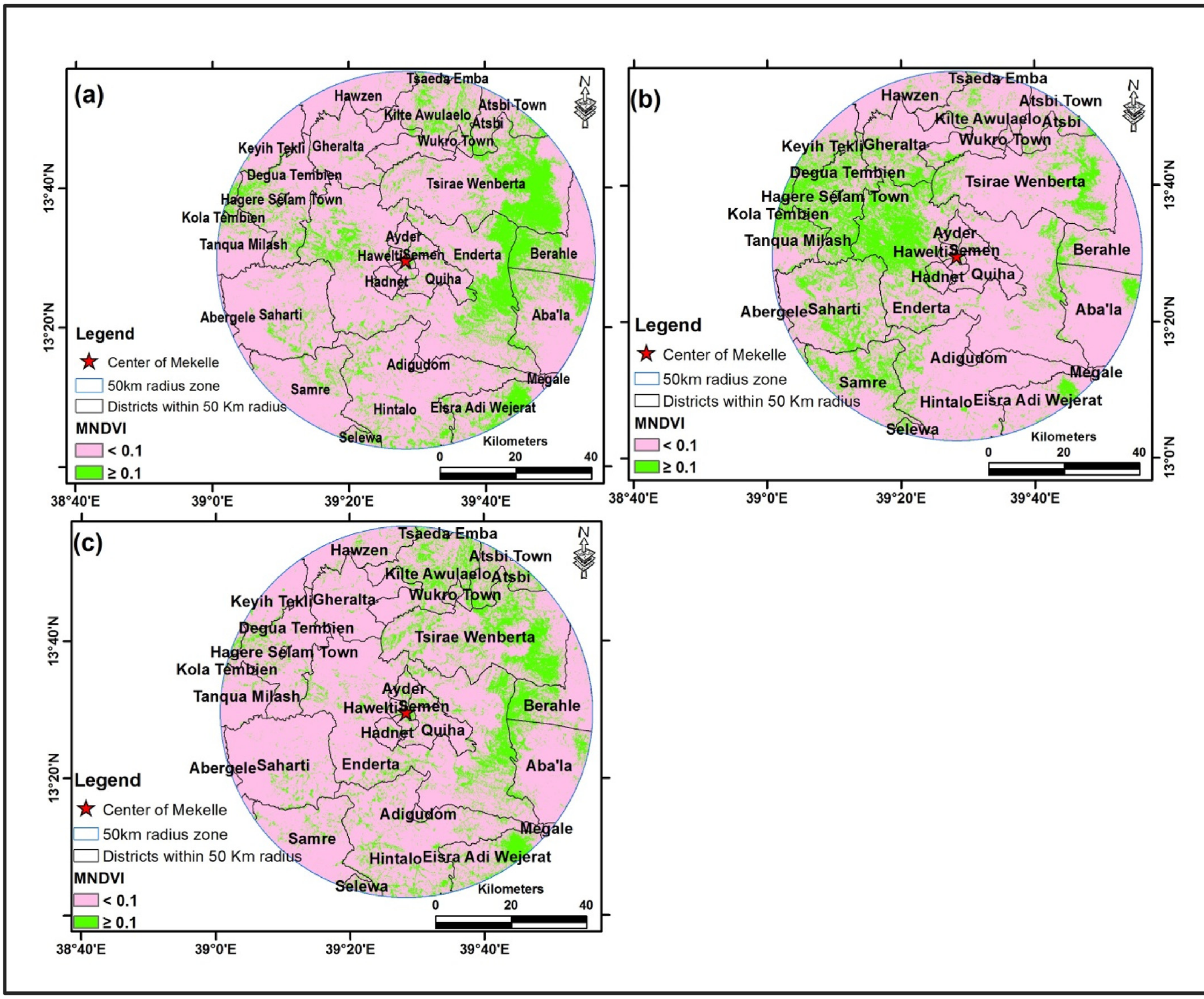

Fig. 2. Spatio-temporal analysis of vegetation indices. (a) MNDVI map of 2000; (b) MNDVI map of 2020; and (c) MNDVI map of 2022.

Table 3
Vegetation density classes based on OSAVI cover changes in different years.

OSAVI density classes	Area in (km^2) and (% of total area examined in this study)			Change in km^2 and (% of total area examined in this study)		Average rate of change in km^2/year	
	2000	2020	2022	2000–2020	2020–2022	2000 –2020	2020 –2022
Low (0.1–0.2)	2991.54 (38.09%)	5896.10 (75.07%)	4838.97 (61.61%)	+2904.56 (+36.98%)	−1057.13 (−13.46%)	+145.23	−528.57
Medium (0.2–0.3)	182.80 (2.33%)	297.35 (3.78%)	314.40 (4.00%)	+114.55 (+1.45%)	+17.05 (+0.21%)	+5.73	+8.51
High (0.3–0.4)	11.33 (0.14%)	14.67 (0.18%)	14.49 (0.18%)	+3.34 (+0.04%)	−0.18 (<−0.01%)	+0.17	−0.09
Very high (> 0.4)	2.14 (0.03%)	0.43 (<0.01%)	0.99 (0.01%)	−1.71 (−0.02%)	+0.47 (<+0.01%)	−0.01	+0.24
Total of vegetation cover area in km^2 (% of total mapped area)	3187.81 (40.59%)	6208.54 (79.05%)	5168.85 (65.79%)	+3020.74 (+38.46%)	−1039.79 (−13.24%)	+151.12	−519.91

Enderta district administration office, 1200 donkey-loads of firewood on non-religious days, and about 2200–2500 donkey-loads of firewood on religious days were supplied daily to Mekelle and Quiha markets. In addition, on average about 1000 sacks of charcoal were supplied to the same marketplaces. The district then applied strict law enforcement on those violating the rules and regulations agreed in 2014. Since this time, community awareness has increased, the supply of charcoal and firewood to the market has been stable, and recovery of vegetation has dramatically improved in the district, until the start of the armed conflict in November 2020.

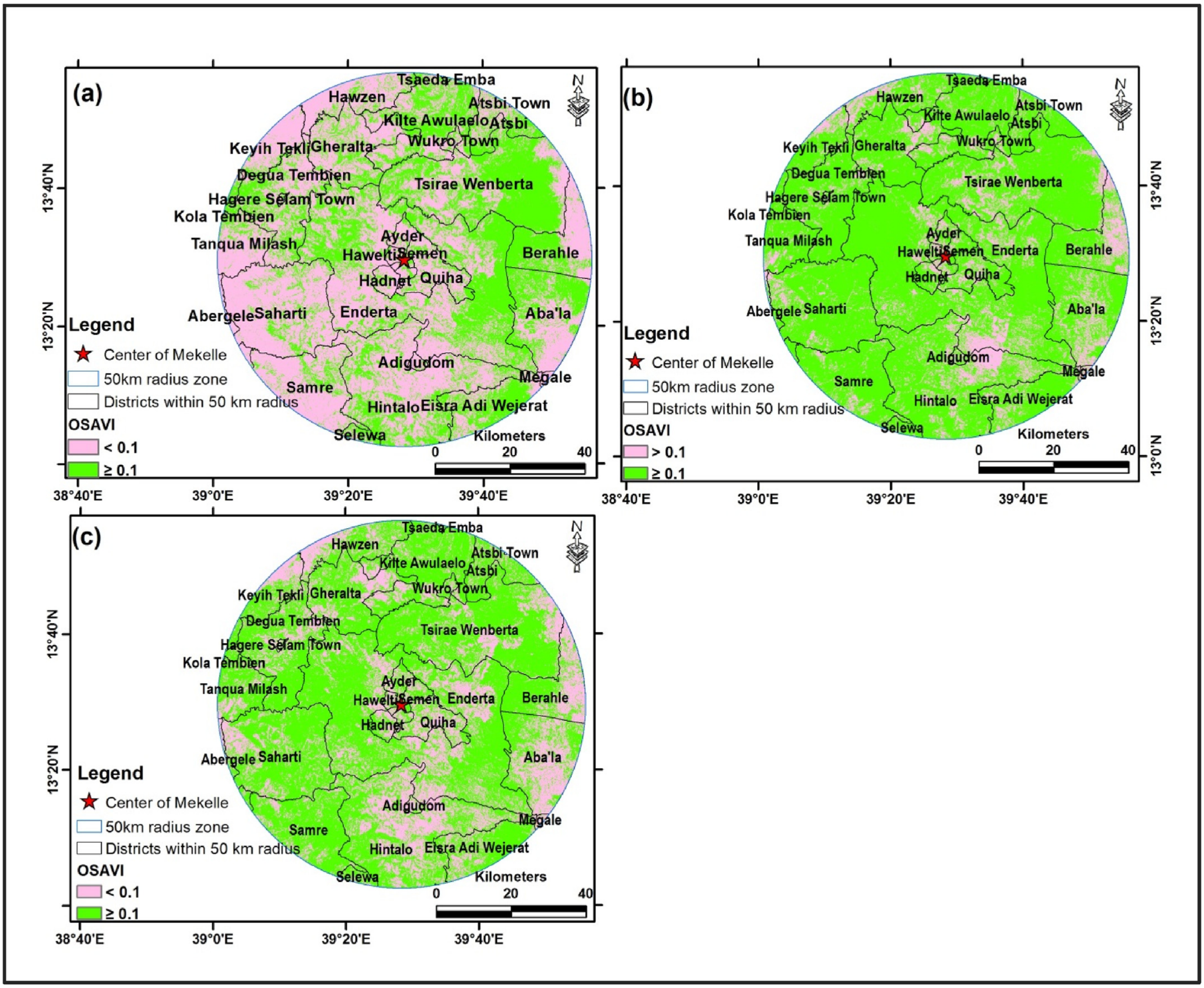

Fig. 3. Spatio-temporal analysis of vegetation indices. (a) OSAVI map of 2000; (b) OSAVI map of 2020; and (c) OSAVI map of 2022.

Before the outbreak of conflict, legal charcoal suppliers were supplying goods to Mekelle by truck from outside Tigray. Firewood harvested from *Eucalpytus* plantations were also supplied to the markets. This was also interrupted by the conflict.

In order to understand the magnitude of deforestation, we assessed the price of charcoal. Before 2020, a 50 kg sack of charcoal was sold between 100 and 150 ETB (1 USD≈30 ETB in 2019) whereas after the conflict started and when electricity was cut off, the same quantity was sold for 800–1000 ETB (1 USD≈42 ETB in 2021). Since the reconnection of electricity to Mekelle with the national power grid in 2022, the price has reduced to 500–700 ETB (1 USD≈52 ETB in 2022). According to an estimate from a supplier, about 10–15 *Acacia* trees are required to fill for a 50 kg sack of charcoal. The branches of the tree can be pruned for firewood and the main trunk used for charcoal preparation in traditional kilns (Fig. 6(a)). The Enderta District administration office identified that charcoal and firewood supply comes from 12 major villages, which are Adezmera, Debre Nazret, Mai Alem, Mai Anbesa, Chelekot (specific place Debre Maerinet), and Mai Genet (west of Mekelle); and Kedamy Woyane, Lemelem, Menbere Kidusan, Meseret, Didiba and Felege Selam (east and southeast of Mekelle). In understanding the recent deforestation issue, the district administration has agreed with village administrations to protect the cutting of trees from enclosed and communal areas. With effect from December 2022, the district has re-strengthened the village level administrations and started to apply the community bylaws again. Moreover, in order to restore the degraded land and vegetation, the free labor campaign for soil and water conservation has restarted on 55 identified watersheds. This conservation programme will be practiced for 30 consecutive days from January 2023 (Fig. 7).

3.5. Analysis of CHIRPS precipitation data

The patterns of mean monthly precipitation (MMP) in the three years 1999, 2019 and 2021 are shown in Fig. 8. As shown in Table 1, satellite images from January and early February from these years were used to analyze the vegetation indices for the subsequent years of 2000, 2020 and 2020. In 1999, the minimum and maximum MMP was 28 and 67 mm, respectively, with a mean value of 50 mm. Higher precipitation values were observed west

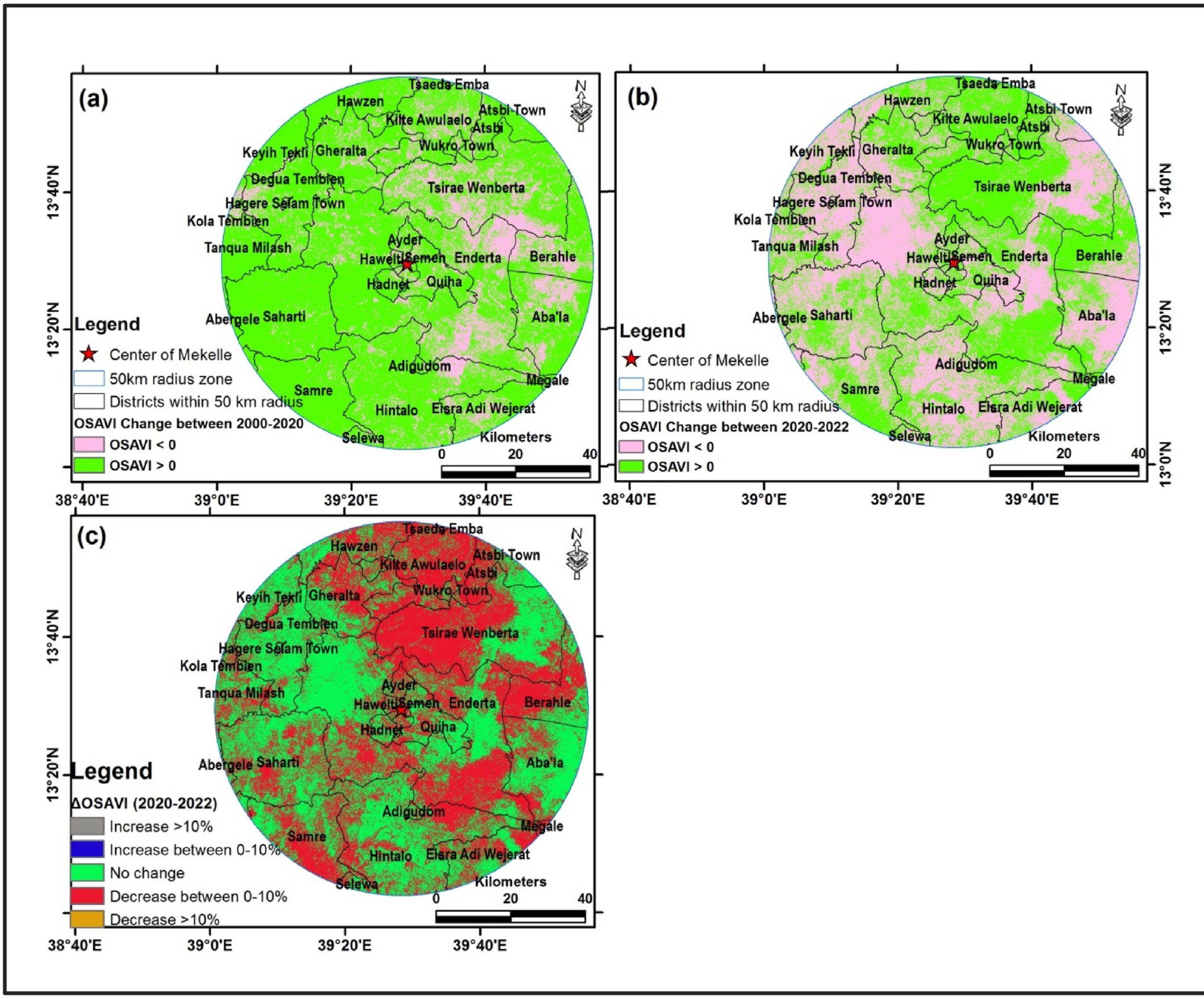

Fig. 4. Difference map of OSAVI. (a) OSAVI change between 2000 and 2020; (b) OSAVI change between 2020 and 2022; (c) ΔOSAVI of 2020–2022.

Table 4
Vegetation density classess based on MAVI cover changes in different years.

MAVI density classes	Area km^2 and (% of the total area examined in this study)			Change km^2 and (% of the total area examined in this study)		Average rate of change km^2/year	
	2000	2020	2022	2000–2020	2020–2022	2000–2020	2020–2022
Low (0.1–0.2)	627.72 (7.99%)	966.45 (12.30%)	682.75 (8.69%)	+338.73 (+4.31%)	−283.70 (−3.61%)	+16.94	−141.85
Medium (0.2–0.3)	20.94 (0.27%)	14.91 (0.19%)	15.79 (0.20%)	−6.03 (−0.08%)	+0.88 (+0.01%)	−0.30	+0.44
High (0.3–0.4)	2.47 (0.03%)	0.06 (<0.01%)	0.28 (<0.01%)	−2.41 (−0.03%)	+0.22 (<+0.01%)	−0.12	+0.11
Very high (> 0.4)	0.21 (<0.01%)	0.00 (0%)	0.01 (<0.01%)	−0.21 (<−0.01%)	+0.01 (<+0.01%)	−0.01	≤ +0.01
Total of vegetation cover area in km^2 (% of total mapped area)	651.34 (8.29%)	981.42 (12.50%)	698.83 (8.90%)	+330.08 (+4.20%)	−282.59 (−3.60%)	+16.51 (+0.21%)	−141.29 (−1.80%)

and south of the study area (Fig. 8(a)). In 2019, the minimum, maximum and mean MMP was 32, 81 and 51 mm, respectively. In this period, higher precipitation was found west of the study area but in a smaller area compared to the other two years (Fig. 8(b)). In 2021, the minimum, maximum and mean MMP was 34, 77, and 57 mm, respectively. Higher precipitation values were observed west of the study area (Fig. 8(c)).

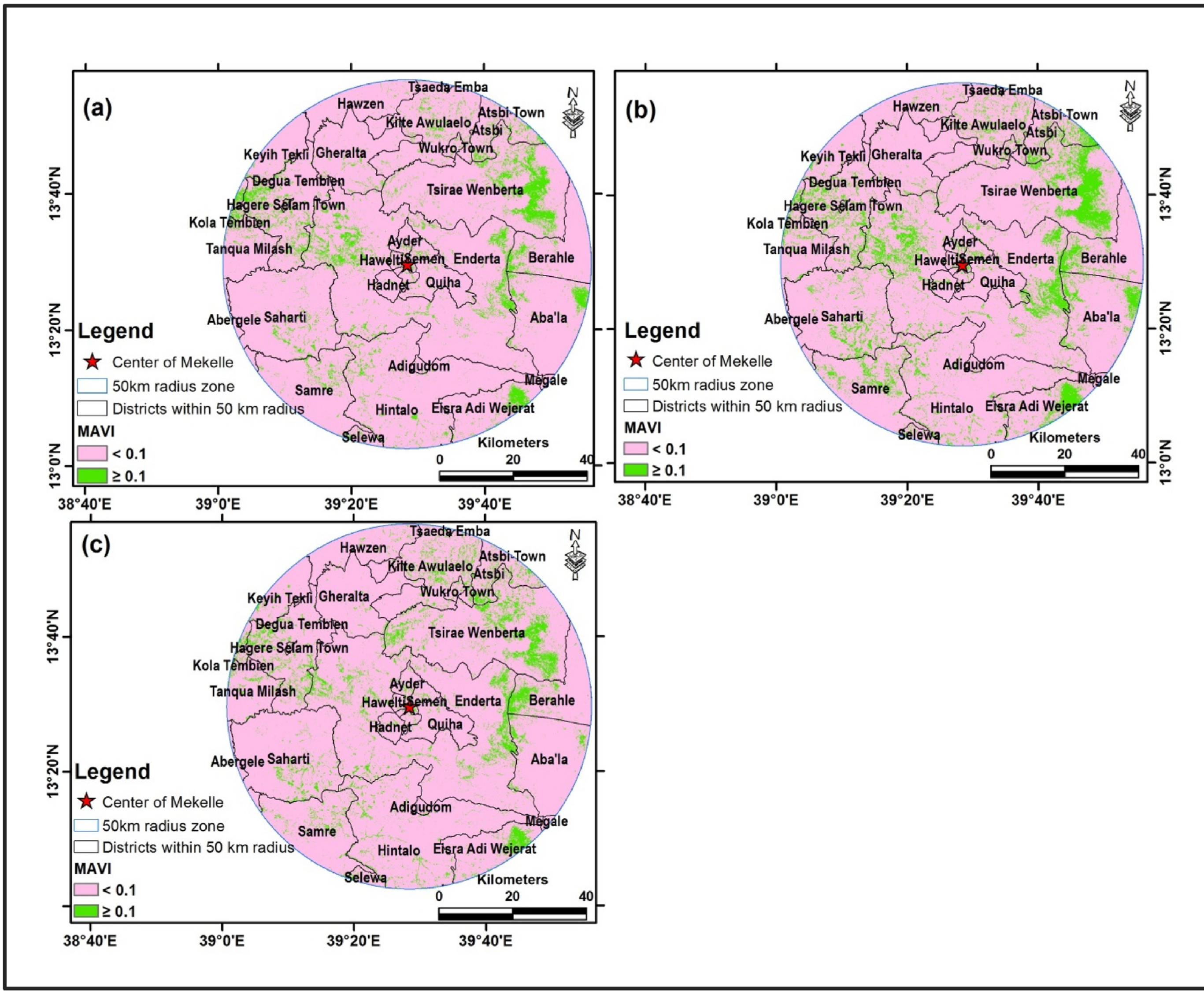

Fig. 5. Spatio-temporal analysis of vegetation index. (a) MAVI map of 2000; (b) MAVI map of 2020; and (c) MAVI map of 2022.

3.6. Relationships between vegetation indices and precipitation

The simple linear regression result for the year 2000 shows that there is no statistical significance at 95% level ($p = 0.067$) between MAVI and MMP. There is a very weak positive correlation between MAVI (2020) and MMP (2019) ($r = 0.10$) and between MAVI (2022) and MMR (2021) ($r = 0.040$). There is also a very weak negative correlation between MNDVI (2000) and MMP (1999) ($r = -0.18$, $R^2 = 0.032$). This very weak correlation might indicate that precipitation is not the only determining factor for vegetation health in the area. Other factors such as temperature, solar radiation, topography and soil properties might also play a role in the effective growth of vegetation (Soomro et al., 2021). It also does not account for the role of human activity in vegetation management and agriculture.

The relationship between MNDVI (2020) and MMP (2019) is statistically significant ($p<0.05$) with a weak positive linear correlation ($r = 0.48$, $R^2 = 0.231$) (Fig. 9(a)). As mentioned earlier, the weak correlation might be due to other factors such as temperature, soil fertility and management of enclosure areas that are not included in the regression model. The analysis also shows a very weak negative correlation between MNDVI (2022) and MAP (2021) ($r =$ — 0.24, $R^2 = 0.054$). Moreover, simple linear regressions were also computed between OSAVI as a dependent variable and precipitation as an independent variable for the years 2000, 2020 and 2022. The correlations between OSAVI (2000) and MMP (1999) shows weak negative correlations (OSAVI $= 0.1391 - 0.000927$ MMP, $r = -0.18$, $R^2 = 0.032$). For the year 2020, there was a weak positive correlation between OSAVI and MMP ($r = 0.11$, $R^2 = 0.015$) although this is not statistically significant ($p = 0.095$) (Fig. 9(b)). Finally, no correlation was observed between OSAVI (2022) and MMP (2021) ($r = 0.00$, $R^2 = 0.00$ with $p = 0.995$).

4. Discussion

Assessment of vegetation cover using ground survey data is time taking, costly and not effective across a large area, especially when access may be difficult or dangerous. Remote sensing-derived vegetation indices are preferable and cost-effective means of measuring the characteristics, biomass, and extent of vegetation cover (Fern et al., 2018; Liu et al., 2012; Zou & Mõttus, 2017). The study area is dominated by sparse vegetation cover and agro-

Fig. 6. Firewood harvesting and charcoal production in Enderta district. (**a**) Traditional charcoal kilns practice at Adi Azmera village (December 2022); (**b**) Farmers selling charcoal around St. Gebriel church, Mekelle (July 2022); **(c)** Illegal charcoal produce confiscated by the Enderta District administration office, Quiha (January 2023) (Source: Photos taken by authors).

Fig. 7. Soil and water conservation practice at Dejen village, Enderta District, January 2023. (a) Construction of stone bunds on sloping land; (b) Maintenance of distroyed stone bunds; and (c) After soil and water conservation work, farmers gathered to evaluate the performnce (Source: Photos taken by authors).

ecologically characterized by rain-fed agriculture typical of a semiarid environment. In such an environment, NDVI is not necessarily appropriate to estimate vegetation coverage or distinguish between vegetation types. In this study, MNDVI, OSAVI and MAVI were used as alternative approaches to quantify vegetation cover before and during the conflict period 2020–22, because they consider the roles of other environmental variables. Comparison of values of vegetation cover from the three different indices shows

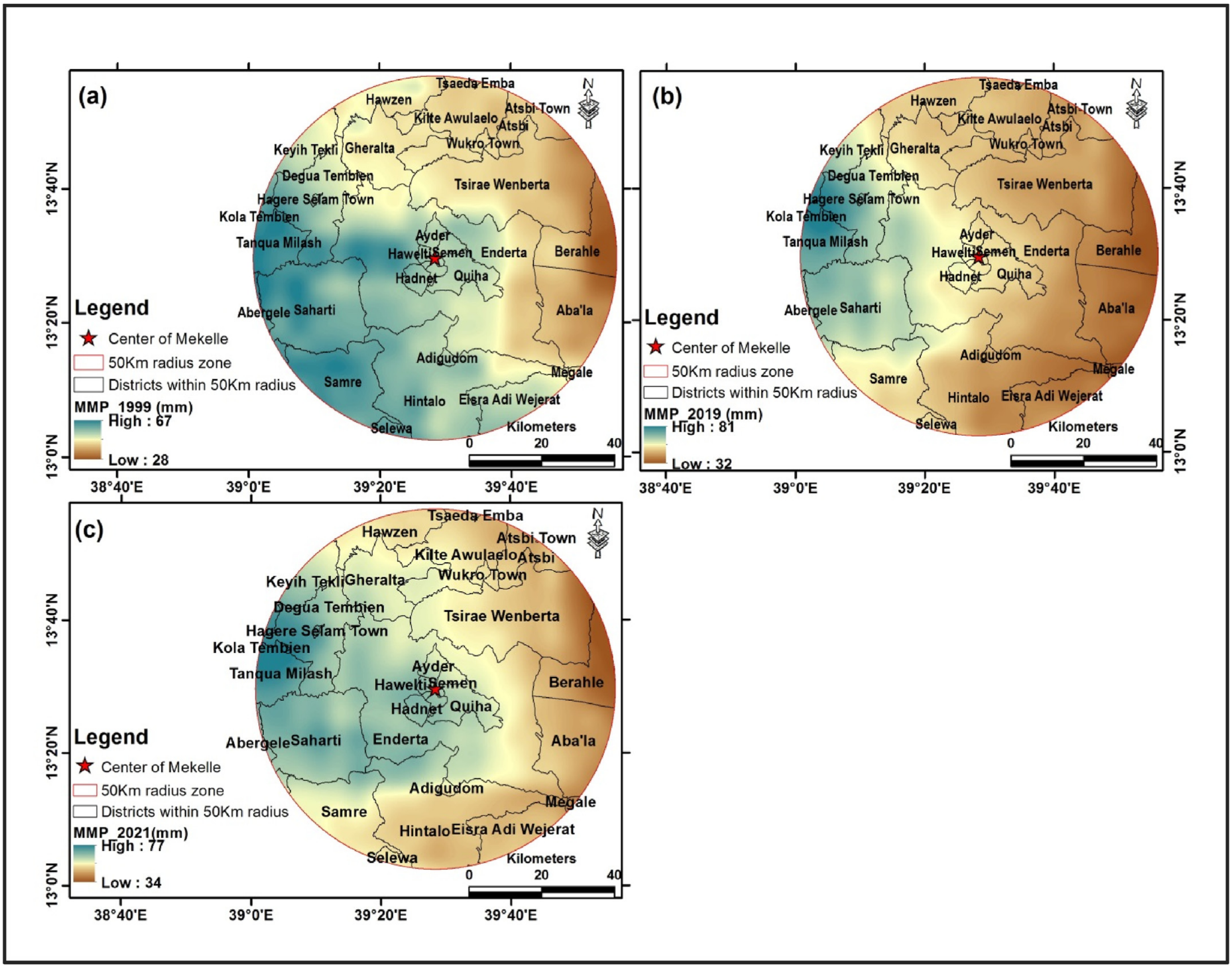

Fig. 8. Mean monthly precipitation (MMP) distribution of the study area computed from the CHIRPS dataset. (a) For the year 1999; (b) for the year 2019; and (c) for the year 2021.

that OSAVI produces the highest cover (40.59% of the study area) with MAVI the lowest (8.29% of the study area). The percentages of high and very high vegetation cover classes are very similar between all indices but this is based on very low absolute values. The greatest variability of the low and (to a lesser extent) medium density classes highlights the sensitivity of low-cover vegetation to disturbance, by human activity or climate change (Lanckriet et al., 2015). Historically, the greatest changes in land cover in Tigray through the 20th Century have been in decreased forest and scrubland with increased bare areas, urban areas and some cropland (Etefa et al., 2018). In more detail and at the local scale in Tigray, changes in cropland density based on Landsat data between 1984 and 2013 show a progressive conversion from higher-density to lower-density agricultural land, attributed to afforestation and land conservation initiatives (Chiemela et al., 2017). However, the classification of low density vegetation cover as identified in this study does not clearly distinguish between different cover types that may include agricultural land that has been either degraded or abandoned, or where agricultural crops have not been harvested, areas of secondary scrub growth, or areas of invasive non-native species such as *Eucalyptus* (Jagger & Pender, 2003). This 'de-intensification' of agriculture appears to be a significant characteristic of the ADLI programme in the period 2000–20. Demissie et al. (2022) examined changes in vegetation cover during the conflict period 2020–21 in Tigray, but using NDVI and Google Earth Engine as analysis tools. Like this present study, they found a mixed picture with some increases and some decreases in NDVI values, attributed to differences in irrigated and unirrigated land, and abandoned and ploughed land. The average rate of change for the medium, high, and very high MNDVI and MAVI density classes showed a decrease before the armed conflict and a slight increase after the conflict. Farmers did not travel far to the remote areas with denser vegetation cover because they were concerned about security. The changes seen in all vegetation indices (ΔOSAVI, ΔMNDVI, and ΔMAVI) for the period 2020–22 show the existence of higher percentages of decreased change followed by no change. The increased change is below 2% in all the vegetation indices. This is a good indicator that the armed conflict has contributed to the decline of vegetation cover in the study area.

4.1. The role of local government and community actors on vegetation resources management

Tigray regional government has designed a strategy to reverse

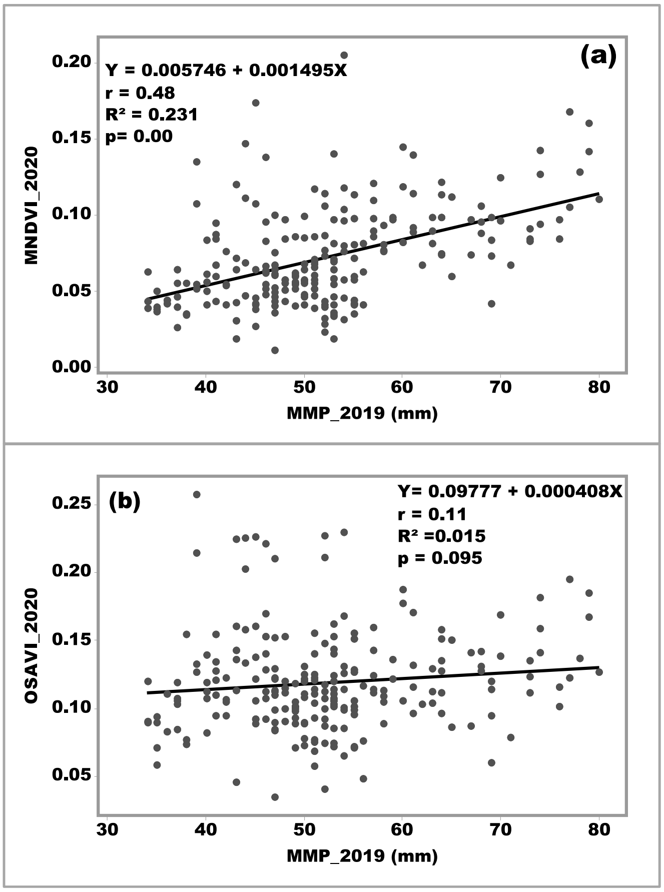

Fig. 9. Scatter plots of simple linear correlation of vegetation indices and precipitation. (a) MNDVI (2020) and MMP (2019); (b) OSAVI (2020) and MMP (2019).

the immediate causes of land degradation in the region (Kahsai, 2015). Over the past three decades, this includes the implementation of development strategies, bottom-up approaches to spatial and agricultural planning, and involvement of different development oriented non-governmental organizations. The well-established system of 20 days' annual free labor of local people to soil and water conservation contributes to tackling land degradation and improving previously degraded areas. At the grass-roots level, rural communities have strong and well-established bylaws for area enclosure protection, watershed management, zero-grazing practices and other communal benefits. During the pre-conflict period, Tigray had therefore made good progress in reversing land degradation and had created a better community understanding and awareness of environmental rehabilitation. The evidence for increased vegetation land cover in the period 2000–20 supports this viewpoint (Tables 2–4). However, the start of conflict in November 2020 immediately changed this well-established institutional system, community bylaws, and social capital of rural communities. Moreover, previously accumulated assets of the rural communities were looted, farm implements were destroyed and burnt (Nyssen et al., 2022); cattle were slaughtered, grain was mixed with soil or burnt, and all these actions resulted in rural food shortages. An outcome was that farmers then started to cut down the restored trees for firewood and charcoal for consumption and for sale in nearby towns and cities such as Mekelle. Other rural residents migrated to towns and cities for better economic opportunities. Table 5 shows the social and institutional situation in Tigray before the conflict (2000–20) and during the conflict (2020–22) and its outcomes in relation to vegetation degradation.

The reinvigoration of the previously-effective water and land management programmes may indicate that there is hope for land restoration and the re-establishment of the rural agricultural economy and forest ecosystem services (e.g. Abera et al., 2020; Gebremeskel et al., 2018; Oniki et al., 2020). Monitoring using remote sensing is necessary to evaluate the success of the water and land management programmes.

However, there are other factors contributing to vegetation cover changes in Tigray including climate change. Over decadal timescales, precipitation is the major control on vegetation (Mucheye et al., 2021) but the relative roles of human activity and climate change vary over time and space across the region (Yang et al., 2022). Annys et al. (2017) argued that other factors like human activity should be considered alongside rainfall variability in woody vegetation development along the Ethiopian Rift Valley escarpment. Other researchers have pointed out that slight decline in precipitation and a sustained increase in temperature in Tigray over the period 2000–20 (Tefera et al., 2020) did not have a significant impact on progressive greening and the spread of vegetated land areas (Tables 2–4). In addition, Demissie et al. (2022) found that land cover change in the conflict period of 2020–22 was controlled by human activity and not by climate. This suggests that, throughout the period of 2000–22 examined in this study, vegetation change was mainly controlled by human activity rather than climate alone. This highlights the role of ADLI and other programmes as a major control on vegetation dynamics and land conservation. These programmes may also help limit the negative effects of any future drying climatic trend in the region.

4.2. Correlation between vegetation indices and precipitation

It was hypothesized that precipitation has a significant relationship with vegetation greenness. According to Evans (1996) correlation strength classification, for MNDVI and MAVI indices in the period 2020, the correlation analysis shows the existence of weak positive relationships between vegetation and precipitation and no correlation for OSAVI index in the period 2020. On the other hand, there was a weak negative correlation was observed in the period 2000 and 22. The negative correlation results are in agreement with the finding of Cui et al. (2018) in the Yangtze River (China). Even though precipitation has a direct influence on vegetation greenness, other factors such as temperature, soil fertility and land management practices also have a role on vegetation health. The absence of appropriate land management during the conflict period aggravated the decline of vegetation cover in the study area. Over the last three decades, Tigray's land restoration policy, which included a wide range of measures, has made a substantial contribution to landscape greening. In general, precipitation cannot be considered as the only limiting factor for plant growth that is other variables becomes increasingly important.

5. Conclusions

Over the past three decades, after the fall of the Derg regime in 1991, the conservation-based Agricultural Development-Led Industrialization (ADLI) policy, enforcement of community bylaws, commitment of the regional government and rural communities, and NGO involvement in sustainable land management in the Tigray region have contributed to the effective implementation of degraded landscape restoration practices. These efforts made Tigray the UN-backed future policy award in 2017. However, since November 2020, the armed conflict in Tigray has contributed to a substantial decrease in forest cover and ecosystem resources. The

Table 5
The remediation and restoration of vegetation resources in the pre-conflict period in Tigray, during the conflict, and the effects of the conflict on institutional systems and vegetation resources management.

Pre-conflict (2000–20)	During the conflict (2020–22)	Effects of the conflict
• **Productive Safety Net Program (PSNP), and Sustainable Land Management programme (SLM) were implemented at the grass-roots level**	• PSNP and SLM activities were interrupted	• Proper watershed management practices and expansion of small scale irrigation development to enhance food security were interrupted
• **Area enclosures were protected from livestock and human activities and zero grazing was used as the most beneficial land rehabilitation mechanism** • **Proper watershed management practices were applied**	• Free grazing become dominant, cutting of trees for military defense construction, cooking and heating and cutting of trees by farmers for firewood and charcoal sale • Watershed management practices such as soil and water conservation were interrupted	• Vegetation degradation was evidenced from remote sensing data • Soil and water resources conservation decreased, with decreased crop and fodder production
• **Effective application of community bylaws and government laws on natural resources conservation** • **20 days' free labor work implemented annually for soil and water conservation and bringing evident positive changes on ecosystem and household living condition.**	• All institutional actors working on remediation and restoration become weak and non-functional • 20 days' free labor was interrupted	• Natural resources conservation practice was interrupted and governmental and community bylaws were violated • The restored vegetation and different conservation structures constructed over the past three decades were destroyed
• **Smallholder farmers accumulated assets for their livelihood improvement** • **Proper cultivation and use of fertilizers and seeds to enhance productivity was possible** • **Increase in fodder production on cultivated land and enclosure areas** • **Expansion of small scale irrigation development to enhance food security** • **Improved livelihoods of rural communities**	• Looting of farmers' means of production, such as livestock, farm implements and grain • Burning crop fields during heavy shelling, air and drone strikes • Shelling from heavy artillery destructed the fodders and rangelands areas. • Small scale irrigation infrastructure were destroyed resulting in interruption of irrigation systems • Agricultural production and incomes drastically decreased	• Farmers exposed to food insecurity and starvation • Reduction of crop production and farmers are unable to return their loans • Reduction of fodder to livestock due to burning and vegetation degradation • Lack of availability of irrigation products, and prices were increased • Rural communities are exposed to food shortages and health and social impact
• **Existence of sustainable power supply systems in the region**	• Disruption of electricity supply and disconnection of the Tigray region from the national grid	• Urban dwellers are forced to use firewood and charcoal for cooking and heating
• **Better understanding of rural communities on protection of the environment** • **Existence of strong social capital at village and district levels**	• Rural communities forced to use the environmental resources • Social issues resulting from the breakup or tensions within rural communities	• Enhanced vegetation degradation due to lack of alternatives for food and income • Social capital is getting weak and farmers become poorer

practices of soil and water conservation measures, zero grazing, enclosure and tree planting have been interrupted because of the conflict. Instead, farmers were compelled to cut down trees and shrubs that had recovered in the previous 20 years in order to support their livelihoods. High demand of wood and charcoal fuel for cooking, heating and other domestic uses during the electricity crisis in Tigray and Mekelle city resulted in notable forest area decrease.

Three vegetation indices (MNDVI, OSAVI, and MAVI) were chosen to analyze vegetation cover change for the years 2000, 2020, and 2022. The results show an overall increase of vegetation cover of different density levels for the period 2000–20. During the war in Tigray in 2020–22, a declining trend in vegetation cover was observed in all indices and this largely reversed the gains of the previous 20 years. This shows how much and how quickly armed conflict can impact directly and indirectly on the natural environment. In 2020 there was a weak positive correlation ($R^2 = 0.015$) between OSAVI and precipitation, and between MAVI and precipitation ($R^2 = 0.008$). The relationship between MNDVI and precipitation ($R^2 = 0.231$) was the only one that was statistically significant at the $p < 0.05$ level. This indicates that precipitation is not the only determining factor for vegetation health. Other factors such as land management practices, temperature, solar radiation, topography and soil properties may also play a role.

To promote positive trends of vegetation growth and reforestation requires formal and traditional institutional development at a grass-roots level, donor involvement in future restoration projects, and an integrated socio-ecological development plan of the region that is inclusive of ecosystem services. Allocation of significant funding by government and non-governmental organizations is required in post-conflict reconstruction to restore the conflict-impacted degraded environment. Vegetation restoration can also promote food and economic security and improved ecosystem services, with positive influences on socio-economic conditions and livelihood opportunities of local communities.

Competing interests of authors

The authors declare no competing interests.

CRediT authorship contribution statement

Solomon Hishe: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. **Eskinder Gidey:** Data curation, Formal analysis, Writing – review & editing. **Amanuel Zenebe:** Formal analysis, Writing – review & editing. **Woldeamlak Bewket:** Writing – review & editing. **James Lyimo:** Formal analysis, Writing – review & editing. **Jasper Knight:** Conceptualization, Data curation, Formal analysis, Methodology. **Tsegay Gebretekle:** Conceptualization, Data curation.

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