



Geospatial solutions for evaluating the impact of the Tigray conflict on farming

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Abstract

Military conflicts strongly affect agricultural activities. This has strong implications for people's livelihoods when agriculture is the backbone of the economy. We assessed the effect of the Tigray conflict on farming activities using freely available remote sensing data. For detecting greenness, a normalized difference vegetation Index (NDVI) was analyzed in Google Earth Engine (GEE) using Sentinel 2 satellite images acquired in the pre-war (2020) and during war (2021) spring seasons. CHIRPS data were analyzed in GEE to understand the rainfall conditions. The NDVI of 2020 showed that farmlands were poorly covered with vegetation. However, in 2021, vegetation cover existed in the same season. The NDVI changes stretched from -0.72 to 0.83 . The changes in greenness were categorized as increase (2167 km^2), some increase ($18,386 \text{ km}^2$), no change (1.6 km^2), some decrease (8269 km^2), and decrease (362 km^2). Overall, 72% of the farmlands have seen increases in green vegetation before crops started to grow in 2021. Scattered patches with decreases in vegetation cover correspond to irrigation farms and spring-cropping rain-fed farms uncultivated in 2021. There was no clear pattern of changes in vegetation cover as a function of agro-climatic conditions. The precipitation analysis shows less rainfall in 2021 as compared to 2020, indicating that precipitation has not been an important factor. The conflict is most responsible for fallowing farmlands covered with weeds in the spring season of 2021. The use of freely accessible remote sensing data helps recognizing absence of ploughing in crisis times.

Keywords Remote sensing · Farming activities · Resilience · Vegetation Index · Humanitarian crisis · War

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Introduction

War is one of the most important factors that adversely affect land use in general and agricultural activities in particular (Gibson 2012; Ransom and Sutch 1975; Robinson and Sutherland 2002; Yusufi 1988). The effects of war on agriculture go beyond the destruction of farmlands, for instance due to the explosion of bombs, travel of tanks over farmlands, bombardment of farmlands with heavy weapons, and use of farmlands as fortifications. Often, resources and infrastructure also are destroyed, including irrigation systems, roads, bridges, farming oxen, and tractors. The impact also extends to young and adult men conscripted or drafted into military services, and consequently are no longer present to tend fields. Beyond this, war causes abandonment of farmlands due to inability of farmers to attend their farmlands, leading to the complete deficiency of agricultural production (Gibson 2012; de Beurs and Henebry 2010).

Conflict has deep historical roots in the horn of Africa. One of the most recent conflicts is occurring in Tigray, Ethiopia's northernmost region, since late 2020. The conflict has resulted in one of the most severe humanitarian catastrophes of the past decade (Annys et al. 2021; Bedaso 2021; Nyssen 2021). Intense war took place in all parts of the region and destruction and looting was omnipresent. By the time the war started (on November 4, 2020), farmers were harvesting their crops in the midst of desert locust infestation. Unfortunately, the war was so intense that crops were not harvested properly (Nyssen et al. 2021a). As the war continued in a withering way, damages on irrigation systems, oxen, farming tool, and death and migration of the rural people were inevitable. Farming activities might have been severely affected due to inability of farmers to plough their farmland in spring 2021, when they should have prepared the lands for sowing by the start of the rainy season. Moreover, both large-scale and small-scale irrigation farms were also severely affected, where in some case like in Wolkait Sugar Factory farmlands have completely dried out and in most other areas farmers had to shift from planting cash crops to cereals.

In most cases, the damages caused and the effects of war are evaluated in terms of direct costs or losses at a specific time (Lindgren 2004). Similarly, post-conflict damage assessments focus usually on damages in industries, services, infrastructures, and facilities in cities, whereas the agricultural sector is the main sector of livelihood in developing countries. Even if assessments are made on agriculture, their focus is mostly on crop losses, forgetting the effect of wars on land management (World Bank 2006). Due to wars, farmers abandon their land and fail to manage it for the next production season. Farmland abandonment, in the context of this study, refers to the inability of farmers to prepare their land for the next production season due to lack of access to their land, damages caused to their farming materials, such as oxen, ploughing tools, houses, and irrigation systems (Brück and Schindler 2009; Darwish et al. 2009).

This study assesses the impact of the conflict in the Tigray region on farming activities, using open access remote sensing data and open source solutions. The main objective was to assess whether the ploughed and fallowed areas, as estimated using satellite images, have changed because of the conflict. For this, we contrasted Sentinel 2-derived NDVI data from pre-war year 2020 and war year 2021, with a temporal focus on the spring season. Hence, the study investigated patterns of fallowed farmlands due to land abandonment during the conflict. Such an approach provides a comprehensive assessment of farmland abandonment due to the conflict and its implication on agricultural activities and the livelihood of the people in the region. The study does not address crop damages, damages to farm implements, irrigation systems, roads and other infrastructure. Lack of

data about the amount and extent of these damages make exclusion of these damages inevitable.

Because of the lack of field data due to the closure of communication services (including internet and telephone), and inaccessibility of the region by any means, remote sensing data provide the best solution to assess the impact of the war on agricultural activities. Satellite image analysis has proven to be effective for analysis of information related to agriculture especially where reliable field data are unavailable. For example, Sentinel images are reliable also because they have high spatial resolution (10 m) and temporal resolution, and provide good ground information (Dannenberg and Kuemmerle 2010). Quantifying patterns of changes in croplands using satellite images has a spatial dimension, contrary to what other field survey data lack (Kuemmerle et al. 2008). Furthermore, satellite images are often freely available and they are cost effective to extract patterns of changes in agricultural activities (de Beurs and Henebry 2010). The assessment was made using NDVI analyzed from Sentinel images. In this study, we answer the questions: (1) Was there increased fallowing during the period of the conflict (2020–2021)? (2) Was the share of ploughed and fallowed land attributable to the war? (3) What are the pathways for using Sentinel and NDVI in recognizing absence of ploughing in crisis times?

Methodology

Study area

Tigray is located between 12.2°–14.9°N and 36.4°–40.0°E with a total land area of 53,065 km² (Fig. 1). The region shares borders with Sudan in the west, Eritrea in the north, the Afar region in the east, and the Amhara region in the south. Tigray has a mountainous and plateau landscape, with elevations rising from 400 to 4000 m a.s.l. Accompanied with cliffs, ledges, and precipices, the mountain ranges are classified as the central highlands, the western lowlands and eastern escarpments (Berhane et al. 2016; Gebremeskel et al. 2018; Gebreyohannes et al. 2013).

According to the Köppen's climate classification (Table 1, Fig. 2), the major climatic classes are AW equatorial (43%), BSh arid (32%), and CWb warm temperate (21%). The average annual rainfall is between 450 and 980 mm (Haftom et al. 2019). Agriculture is the mainstay of the economy in the region. The region's land cover is dominated by farmland (55%) and shrubland (33%) (Admasu et al. 2011). It has a small proportion of forest cover (3.8%) which is mainly the result of the recent efforts of land rehabilitation in the region and old forest reserves in scattered patches and near churches.

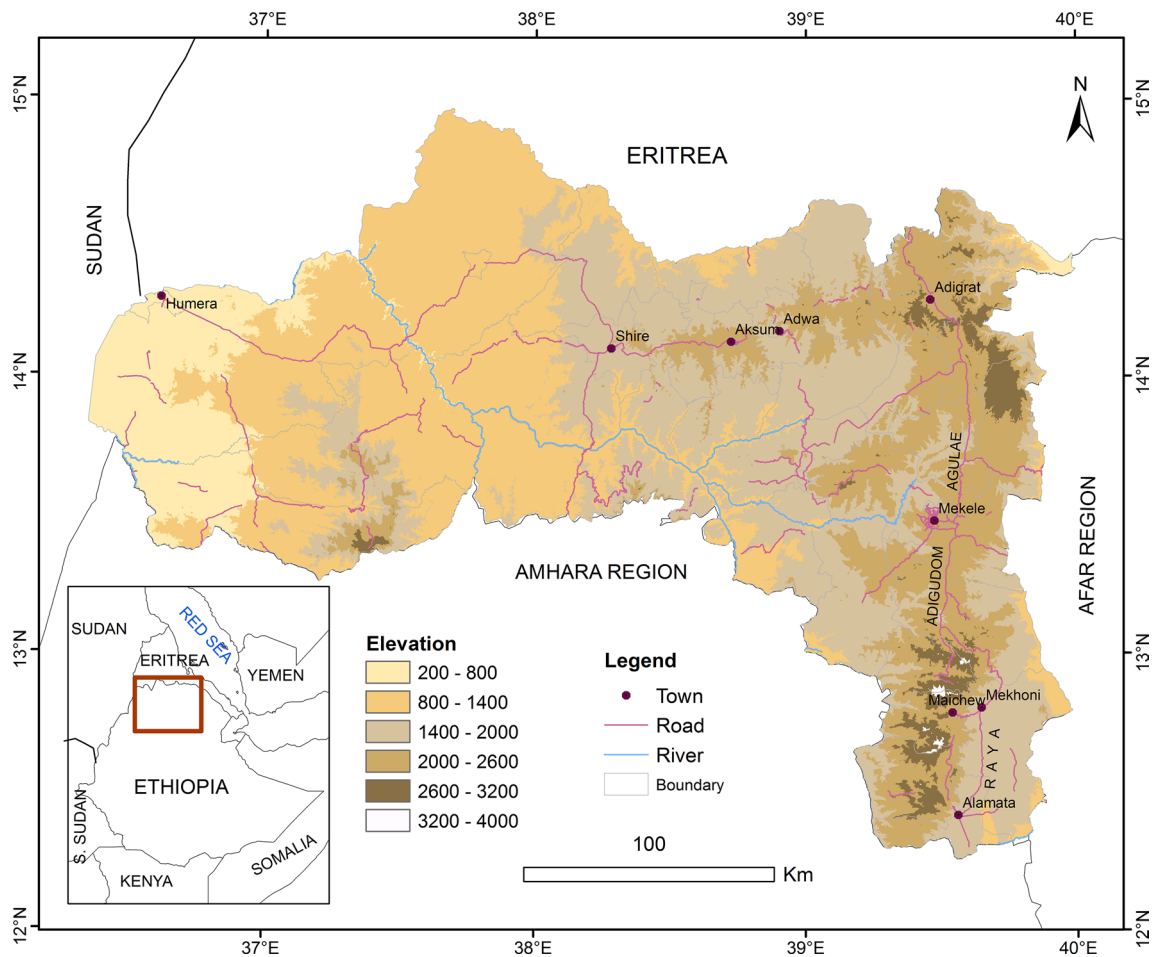


Fig. 1 Location map of the study area

Table 1 Koppen climate classification statistics of Tigray

ID	Koppen climate classification	Area km ²	Proportion (%)
1	Aw equatorial	22,809	43
2	BSh arid	16,658	32
3	BWh arid	80	0
4	CWa warm temperate	2105	4
5	Cwb warm temperate	10,973	21

More than three quarters of the people of Tigray depend on agriculture mainly coming from subsistence farming (Regional State of Tigray 2018). Farmers typically prepare their land during the spring season (March–May) for cropping during the summer rainy season (Gebrehiwot et al. 2022; Tsegay et al. 2019). The farmers start their preparation even earlier than March, as the land preparation requires ploughing multiple times (Gebreegziabher et al. 2009). With this, on average, the start of the growing period is June in most parts of the region (Annys et al. 2021). In some areas

along the western Escarpment of the Rift Valley, along the Danakil depression, farmers produce fast-growing crops (such as tef, wheat, and maize) using the small rain in the spring season (Jacob et al. 2019). These farmers start preparing the farmlands that were used for spring season cropping in May for cropping in June and July. During the spring season, repetitive ploughing is the main practice to remove weeds so that the seed bank in farmland soils gets almost exhausted before sowing occurs. Ploughing is also seen as a way of improving soil productivity. When fields are ploughed immediately after harvesting, the crop residues are incorporated into the soil to improve soil fertility. Farmers also do some ploughing after planting to destroy weeds. The frequency of ploughing varies from two to five times, depending on the type and variety of crops (Gebreegziabher et al. 2009; Nyssen et al. 2011). Hence, during the spring season and at the beginning of the summer season (March to June), most of the farmlands are ploughed. By the end of this period, there is hardly any land left for following. The main production season comes immediately, and cropland should be ploughed and prepared for sowing. However, in a

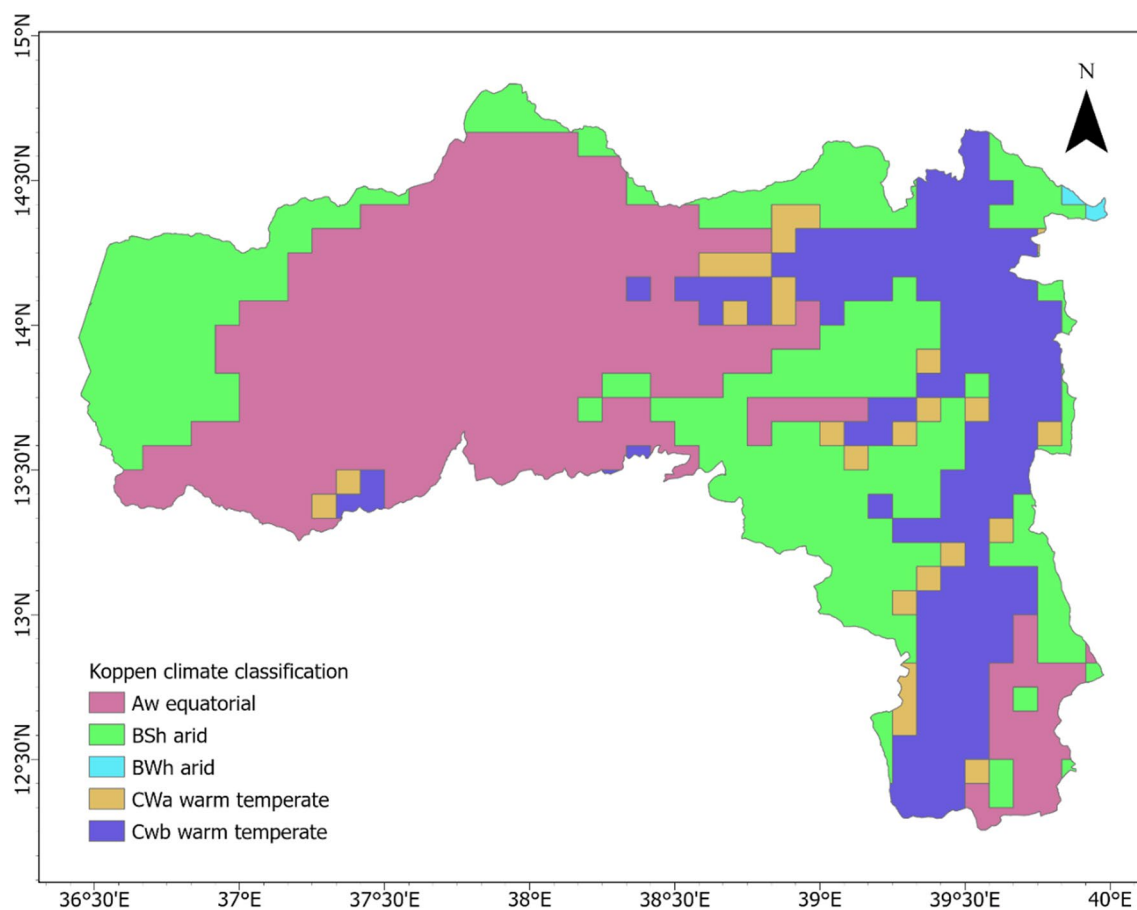


Fig. 2 Climatic zones of Tigray according to Koppen's climate classification. *Source:* <http://koeppen-geiger.vu-wien.ac.at/present.htm>

normal course of land management, there may be some areas in the southern part of the region that may have crop covers (sorghum) by the end of June, as the climate is wetter and allows early sowing (Frankl et al. 2013).

Data acquisition for 2020 and 2021

For data selection and acquisition, the period from April 15 to June 10 was selected because land preparation and sowing activities take place in this period in Tigray. A comparison of satellite images of the same period for 2020 and 2021 was carried out. Hence, Sentinel 2 Satellite images (10 m spatial resolution and 5 days temporal resolution) with a cloud cover of less than 5% for 2021 and cloud cover less than 2% for 2020 that cover the study area were obtained (Lang et al. 2019; Yang et al. 2017). The Sentinel images were extracted using Google Earth Engine. A median value was used to select the images (bands 2, 3, 4, and 8) with less than the defined cloud cover. The stacking and mosaicking of image tiles also were carried out using Google Earth Engine.

In order to analyze and compare the climatic conditions of the 2020 and 2021 spring seasons, we used the Climate

Hazards Group Infrared Precipitation with Station data (CHIRPS), a more than 30-year quasi-global rainfall dataset. The CHIRPS data incorporate in situ station data to create gridded rainfall time series (5.5 km spatial resolution) for trend analysis and seasonal drought monitoring (Funk et al. 2015). The data were analyzed in Google Earth Engine, R, ArcGIS, and QGIS environments.

Mapping farmlands

In order to extract agricultural land, we used the land cover classification we made in 2020 using Landsat imagery of 2019. Landsat 8 OLI/TIRS scenes that were acquired during the dry season (January) of 2019 were used for land cover classification. We used 150 GPS points that were collected during the dry season of 2019 for ground truthing. The SRTM Digital Elevation Model (DEM) with 30 m spatial resolution was used for Topographic correction of the Landsat images. Even though the study area is large and small numbers of ground truthing data were collected, they sufficiently represented each land cover class. Among the existing classification methods, the widely used Maximum

Likelihood Classification method was used (Otukey and Blaschke 2010). The Maximum Likelihood Classification method is most widely used supervised classification in a variety of applications (Sisodia et al. 2014). It computes the class probabilities for each raster cell and assigns the cell to the class with the highest probability value (Otukey and Blaschke 2010; Richards 2005). For implementing the supervised classification, six land cover classes (cropland, bushland, grassland, forest, bareland, and water bodies) were identified based on expert knowledge of the study area and available secondary information in the literature (Adamo et al. 2014). As spectral separation of bareland and built-up areas was difficult, both were merged together and identified as bareland.

For the accuracy assessment, the error matrix and Kappa statistics were analyzed in ERDAS Imagine 2015 software. These are standard accuracy reporting methods. The error matrix is a square array of numbers set out in rows and columns that express the number of sample points assigned to a specific class proportional to the actual class on the ground. It is a very effective way to represent accuracy (Balogun et al. 2020; Congalton and Green 1999). The classification was achieved with an overall accuracy of 91% using 50 training sets (GCPs).

Analyzing vegetation cover

With the aim to detect ploughing and presence of weeds, greenness index was analyzed using the Normalized Difference Vegetation Index (NDVI) in Google Earth Engine. The NDVI is reliable in monitoring the status of vegetation cover and forest biomass. Healthy vegetation has a low reflectance in the visible portion of the electromagnetic spectrum due to chlorophyll and other pigment absorption and has a high reflectance in the NIR because of the internal reflectance by the mesophyll spongy tissue of green leaves (Lunetta et al. 2006; Lunetta and Christopher 1998).

For NDVI analysis, the appropriate bands for the Red and NIR of the Sentinel imagery are bands 3 (Red) and 8 (NIR). The output NDVI values range from -1.0 to $+1.0$ (Ghorbani et al. 2012). NDVI values from 0 to 0.2 correspond to sand, soil or ploughed farmlands; 0.2–0.5 represent sparse vegetation such as shrubs, grasses, or senescing crops; whereas greater than 0.5 correspond to forests or crops at peak growth stage (Ghorbani et al. 2012). Hence, based on NDVI values, it is possible to distinguish one land unit from another.

The changes in greenness between the two years were detected using image differencing (Coppin et al. 2002; Ghorbani et al. 2012) in ERDAS Imagine. In this method, images of the same area, obtained from time steps t_1 and t_2 were subtracted pixel wise:

$$Id(x, y) = I1(x, y) - I2(x, y), \quad (1)$$

where $I1$ and $I2$ are the images obtained at t_1 and t_2 and (x, y) are the coordinates of the pixels. The resulting image, Id , represents the spectral difference of $I1$ from $I2$. This method was used to prepare change maps, with NDVI values ranging between -1 and $+1$. In addition, this map was classified as increased, decreased or no change in NDVI.

Analyzing precipitation patterns

In addition to the effect of the war forcing the farmers to fallow their land, the effect of precipitation conditions on the vegetation cover of the farmlands during the spring seasons of the two years was analyzed as well. In order to map the rainfall patterns, the daily mean and the total precipitation of the 2020 and 2021 spring and early summer seasons (April 15–June 10) were analyzed in Google Earth Engine using the CHIRPS 2.0 quasi-global rainfall dataset (Coppin et al. 2002).

Separating NDVI changes due to rainfall and lack of ploughing

Changes in precipitation and NDVI were analyzed using an image differencing method. A regression analysis was carried out between the changes in precipitation and NDVI, putting, precipitation as a predictor and NDVI as dependent variables. Most of the residual values between the estimated and observed changes in NDVI are distributed between -0.1 and $+0.1$. We used the residual map of the regression analysis to differentiate changes in NDVI that are supposedly attributable to lack of ploughing due to war or other factors such as precipitation (Horn and Lee 2016; Schulte-Hostedde et al. 2005). We took a threshold of 0.01 of the range of the residual values as the smallest deviations between the estimated and observed NDVI values that could come due to precipitation. This threshold is the 10% of the range of the deviations as derived from the coefficient of determination ($R^2 = 0.1$).

Results

Vegetation cover in 2020 and 2021

Generally, as indicated in Fig. 3, in both 2020 and 2021, high NDVI values are predominantly found in the western and the eastern escarpment of the region. The latter area represents the western escarpments of the Rift Valley where elongated and somehow interconnected forest covers are found. That might be related to the endowment of the area for bi-modal rainfall patterns, with small rains in spring between March

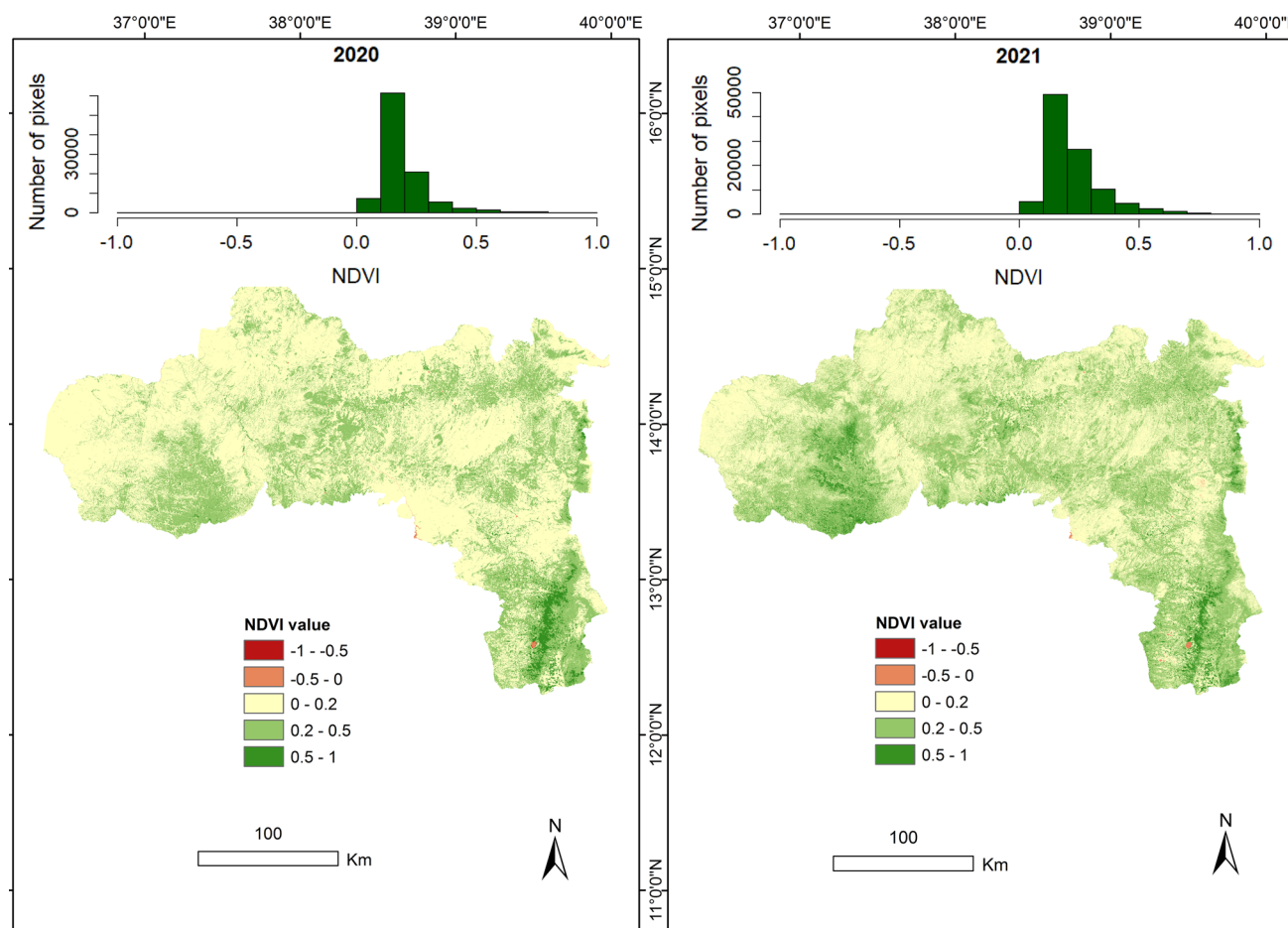


Fig. 3 Overall NDVI values of during the spring season of 2020 (left) and 2021 (right) in Tigray

and May, and high rainfall in the summer season between July and September (Gebrehiwot et al. 2022). As is indicated in the maps in Fig. 2, also according to the definition of different land cover types based on NDVI values, the region is dominated by farmland (NDVI = 0 – 0.2). This value represents croplands that are prepared for cultivation, with no crop or herbaceous cover. The NDVI values between 0.2 and 0.5 represent bushlands, shrublands, grasslands, or well-grown crop covers. Areas covered with herbaceous vegetation and newly grown crops are under this category. In the NDVI map of 2020, we realize that in the period between the end of April and beginning of June, in most areas of the region, less vegetation cover was observed. However, in 2021, we observe more vegetation cover in the same season. That is, areas whose reflectance represented soil or rocks in 2020 are showing green coverage in 2021.

Changes in NDVI between 2020 and 2021

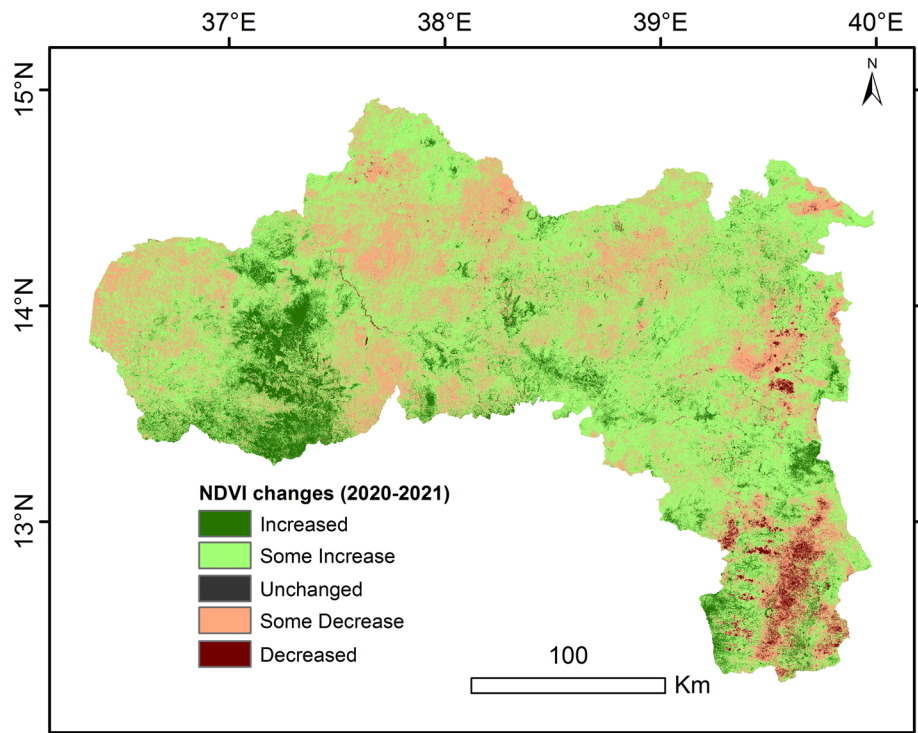
The mean value of the NDVI difference is 0.01 (± 0.04). Even though most of the increases and decreases in NDVI

values of 2020 and 2021 are concentrated between -0.1 and 0.1 , the changes stretch up to -0.72 and 0.83 . This indicates that some areas have shown significant changes in greenness in both directions. The percentage of increase in greenness dominates (72%) over the decrease in greenness (28%) (Table 2). Decreases in greenness are recorded in patches of areas that are spread over the whole region (Fig. 4). This implies that there is no clear pattern of changes

Table 2 The magnitude of change expressed as increase, decrease, and no change

Change	Area (km ²)	Percentage
Increased	5800	10.5
Some increase	33,374	60.7
Unchanged	12	0.02
Some decrease	14,709	26.74
Decreased	1105	2.01
Total	55,000	100

Fig. 4 NDVI change maps between springs of 2020 and 2021: magnitude of changes as increase, decrease, and no change all over Tigray, in croplands and other land uses



in greenness over the region as a function of biophysical and agro-climatic conditions.

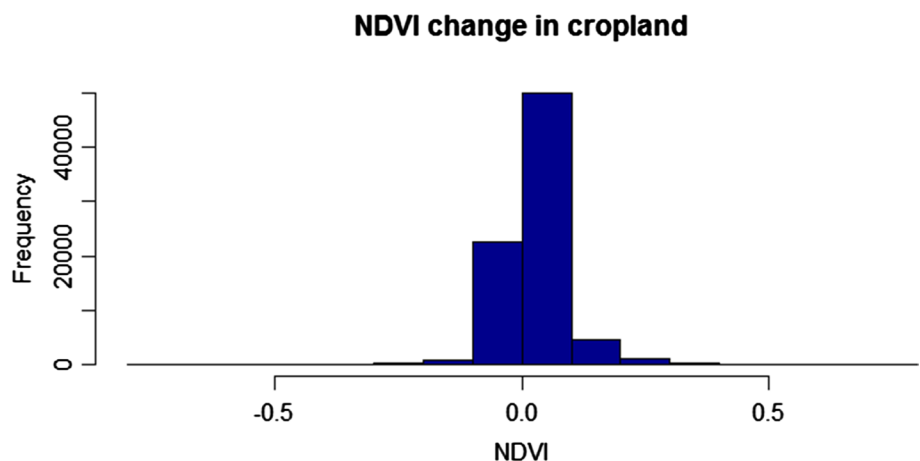
Pattern of vegetation cover in croplands

As the histogram of Fig. 5 depicts, considerable positive changes in greenness are observed from 2020 to 2021. The significant majority of the changes range from 0 to 0.1. Similarly, a decrease in greenness, yet far smaller in size, has taken place with NDVI values ranging from 0 to -0.1 . In total, the changes in NDVI values range from -0.87 (min) to 0.95 (max). Croplands in Tigray region cover $29,186 \text{ km}^2$ (55%) of the total area of the region in 2019. The changes in greenness propagated in farmlands

were explained in four categories, which are increased (2167 km^2), some increase ($18,386 \text{ km}^2$), no change (1.6 km^2), some decrease (8269 km^2), and decreased (362 km^2). This indicates that 71% of the croplands have experienced some green vegetation growth, whereas the remaining 29% experienced a decrease in vegetation cover in 2021 as compared to 2020.

As the spatial pattern of the changes in greenness shows (Fig. 6), most of the farmlands, well distributed all over the region, have shown increases in greenness in the spring season of 2021 as compared to the same season in 2020. Similarly, some areas distributed as scattered patches have shown decreases in greenness.

Fig. 5 Histogram of the distribution of changes in NDVI between 2020 and 2021



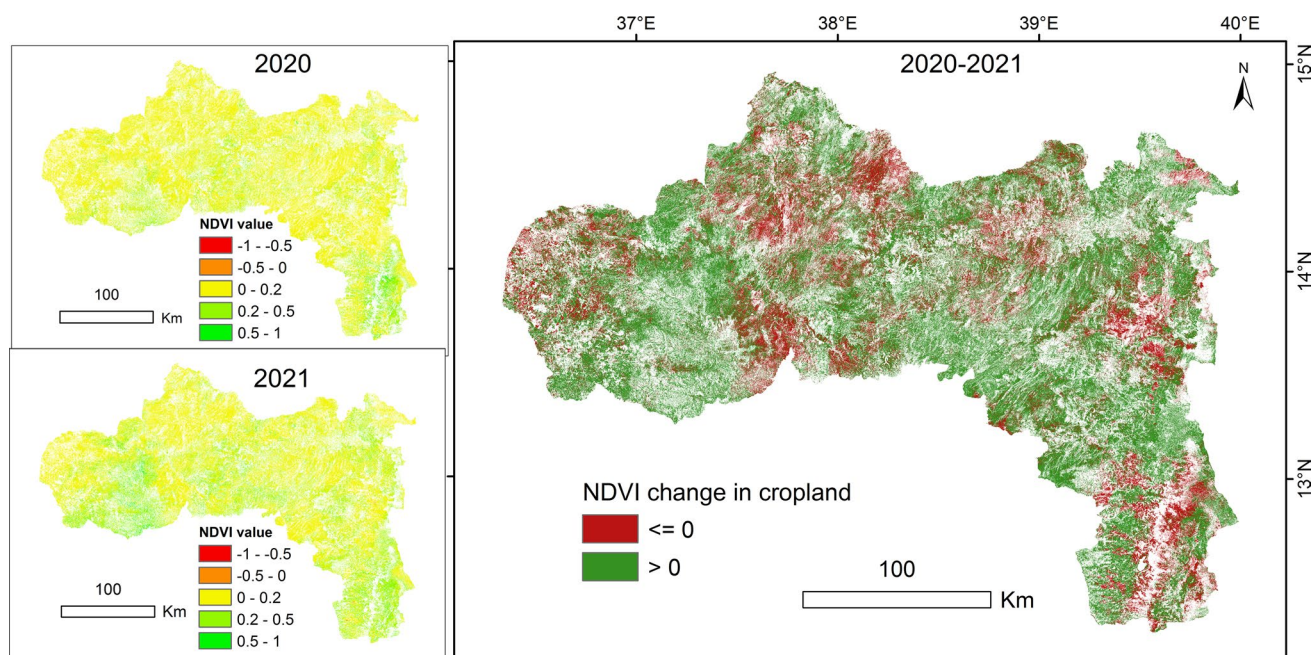


Fig. 6 NDVI changes for croplands only. The right map shows negative and positive changes. The negative changes are decreases in greenness, whereas positive changes represent increase in greenness. White areas represent other land cover types

Discussion

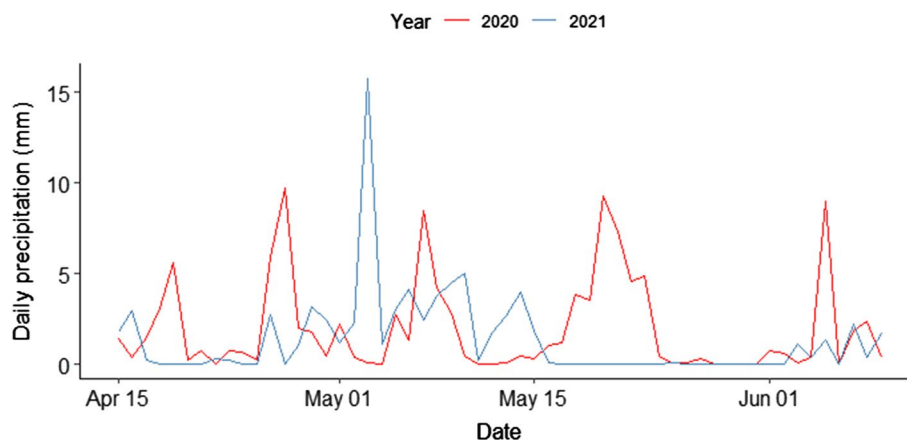
Vegetation pattern over the period of the war

Generally, vegetation cover, expressed in terms of greenness seems more skewed to the right in 2021 as compared to 2020. A general increase in greenness is observed between the two years. One of the most important factors that could probably be responsible for the increase in greenness is precipitation conditions during the spring season of the two years. Hence, in order to see whether the variability of the spring rainfall is responsible, we analyzed the mean daily precipitation for the spring and

the beginning of the summer seasons (April 15–June 10) of 2020 and 2021 based on the CHIRPS 2.0 dataset (Funk et al. 2015). Even though an increase in greenness is observed in the region, during the spring seasons of 2020 and 2021, the rainfall pattern shows a lower rainfall receipt in 2021 compared to 2020 (Figs. 7, 8). The mean seasonal rainfall was 111 mm (± 48) in 2020, whereas it dropped to 76 mm (± 33) in 2021 (Table 3). Hence, the change in rainfall amount was not an important factor for the increase in greenness in the spring seasons of 2021, during the time when the conflict was going on.

Moreover, as Fig. 7 shows, the mean daily rainfall reached its maximum on May 3 in 2021 with > 15 mm, and dropped to < 1 in 2020. There were a few records

Fig. 7 Daily rainfall (April 15–June 10) of 2020 and 2021 of the Tigray region (averaged)



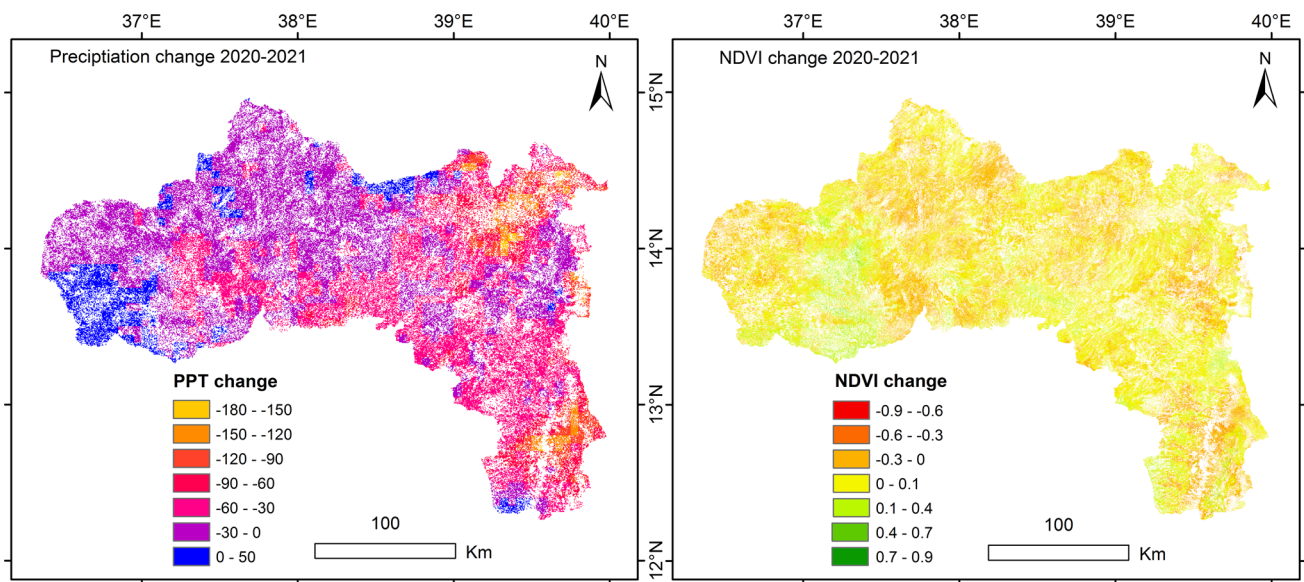


Fig. 8 Spatial pattern of seasonal rainfall (in mm) and NDVI changes in agricultural land (2020–2021)

Table 3 Summary of the total seasonal rainfall in 2020 and 2021 (April 15–June 10)

Year	Mean	Min	Max	Std
2020	111	20	336	48
2021	76	15	242	33

between 5 and 2 mm in 2021 up to mid of May, whereas there were records greater than 2 mm with maximum of nearly 10 mm in more than 20 days (between April 15 and June 10) in 2020. This clearly shows that the rainfall amount and distribution over the spring period in 2020 were better than in 2021. A regression analysis depicted that rainfall was not a main factor of changes in NDVI in croplands ($R^2 = 0.1$). The visual interpretation of Fig. 8 shows that in most areas where a local decrease in rainfall is recorded in 2021 as compared to 2020, local increases in NDVI values are observed. Hence, the conflict, that left croplands fallowed and covered with herbaceous plants, grasses, and growths from crop ruminants of the previous cropping season should be responsible.

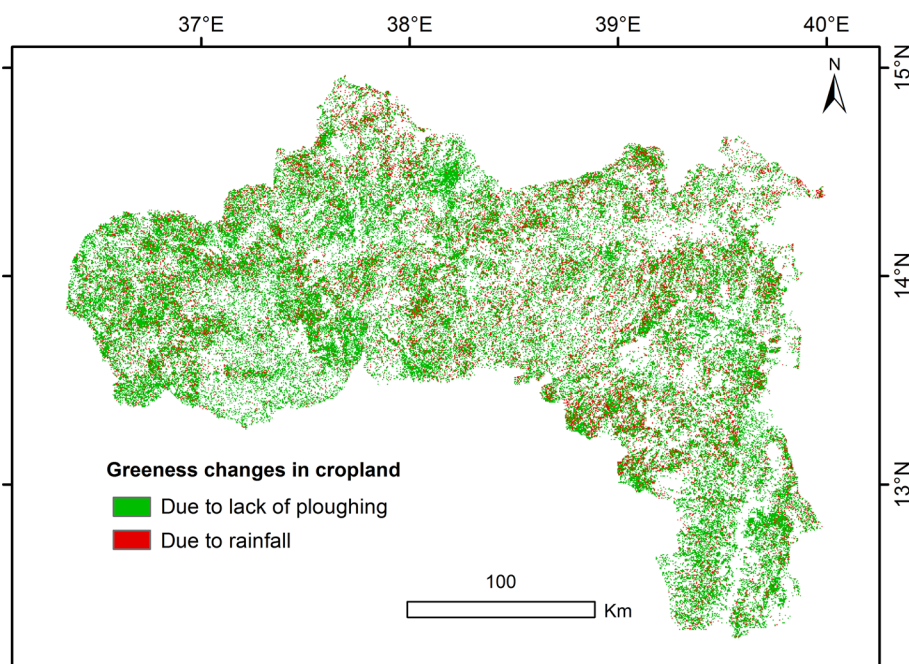
Using the residuals of the deviation between the observed and estimated NDVI, we detected NDVI changes in agricultural areas as caused by rainfall and lack of ploughing due to the war (Fig. 9). The vegetation cover change in the spring season of the larger proportion of the croplands (23,824 km², 82%) was due to lack of ploughing. The remaining 18% (5362 km²) was due to rainfall. Hence, failure of farmers to prepare their farmlands during the spring season due to the war was the major factor.

The impact on farming activities

As the growing period depends on rainfall conditions of the short rain spring season that determines the soil moisture condition to last up to the main rainy season (Frankl et al. 2013), farmers will have a good crop growth in July with crops that have long growing period, such as sorghum, maize, and finger millet (Frankl et al. 2013). These crops grow well in July (Fig. 10c), whereas the months before are crucial for ploughing, preparation and sowing (Pender and Gebremedhin 2006). In this period of the year farmlands with bare soil and no greenness were expected. Nonetheless, greenness has increased over farmlands during the period of the conflict signifying the growth of weeds. As the most dominant land use we realize that in the period between the end of April and the beginning of June 2020, in most areas of the region, farmlands were not well covered with vegetation, either crops, herbs, or grasses. However, in 2021, we observe more vegetation cover in the same season. Farmlands, represented by exposed soil in 2020, are showing green coverage in 2021.

The conflict started in the season when farmers were harvesting their crops in autumn (November 04, 2020) and continued to the spring (March–May) and the summer seasons (June–August) of 2021 when the farmers should plough, sow, and grow crops in the rainy summer season for harvesting in the forthcoming autumn season (Fig. 10a). As some evidences show (Nyssen et al. 2021b), all the farmers were not able to harvest their crops as most of the crops, especially those with long growing season (sorghum, maize and finger millet and some crops sown lately) were not gathered. Farmers were forced to leave their villages and travel

Fig. 9 Vegetation cover change of croplands in the 2021 spring season as caused by precipitation and by lack of ploughing because of the war in Tigray



to towns or stay in a hiding near their villages during the scenes of the war (Abai 2021). Many factors are responsible for the farmers to fail ploughing and preparing their land for the main rainy season. One of the most important factors, as witnessed by many sources, is their failure to stay in their villages and access their land for ploughing. As the war was intensive and elongated, the farmers were forced to leave their villages and migrate to towns and other safe places. In situations where they cannot go to towns, they were hiding in gorges and caves until the war (locally) cooled down. Moreover, lack of farm implements, such as farming tools, fertilizer, seeds, and oxen, aggravated their incapability (Asfaha et al. 2021; Nyssen et al. 2021b; WPF 2021). As our study shows, farmers failed to plough their land for the rainy summer season and the farmlands remained fallowed (Fig. 10d). Later, after the occupation of the majority of the region by the Tigray forces, the large absence of farm implements and inputs was one of the major challenges often quoted by the farmers (WPF 2021).

Hence, the failure to plough their land and leave fallowed has contributed to the growth of weeds on farmlands (Fig. 10b). Most of the farmers who had the economic/labor means started ploughing in June when most areas were occupied by the Tigray forces (ACAPS 2021, 2022). Some farmers have managed to plough their land in May as a typical case shown in Fig. 10b.

On the other hand, in an analysis of changes in greenness in farmlands, a decrease in greenness was observed in some areas. In addition to rain-fed agriculture, irrigation agriculture is practiced and increasing in the last two decades in Tigray (Aseyehgn et al. 2012; Tesfaye et al. 2000). In the

spring seasons, it is common to have well grown crops in irrigation farms (Fig. 11). Moreover, in the western escarpments of the Rift Valley, the spring season is a second cropping season for fast-maturing crops. Hence, in this time, it is common to see well-grown crops with a higher greenness as compared to the surrounding areas (Figs. 11, 12). Hence, the decrease in greenness propagated in some areas is most probably to be in those areas with spring cropping, and irrigation agriculture. The areas other than the eastern escarpments with irrigation practices are covered with crops from March to June. Irrigation areas are mostly ready for rain-fed agriculture after June to use the rainwater in July and August. Nevertheless, due to the war, the irrigation areas that were supposed to be covered with crops are now left uncultivated and consequently a decrease in greenness is observed in the satellite image analysis. Like the rain-fed farmlands, the irrigated farmlands are covered with newly growing weeds. As the greenness of well-grown crop covers is higher than newly grown grasses and herbaceous plants, a decrease in greenness was recorded in these areas.

Using Sentinel and NDVI in recognizing absence of ploughing in crisis times

During war times, accessing information about its impacts is less possible. Moreover, due to wide spatial coverage of war fronts gathering ground-based information over a large area is implausible. As a result, during the war, information about the impacts of war on land resources, such as agriculture is scarce. The use of open access remote sensing data during conflicts is a best option. Satellite image analysis has

Fig. 10 Temporal patterns of cropping: **a** farmlands ploughed and prepared for sowing in the rainy season (May 2015) in the Raya graben bottom; **b** farmland in May 2021, a farmer determined to start ploughing his land near Agulae. His land and the surrounding farms show weed growth. This farmer was interviewed by Radio France International (RFI 2021). ©Sébastien Nemeth / RFI (published with permission); **c** a farmland with crop (sorghum) growth in July 2015 in the Raya graben bottom, and **d** farmland in August 2021 around Adigudom. Most lands are recently ploughed and their crops are in early growth



Fig. 11 Irrigation agriculture in the Raya graben (southern Tigray) in March (Demissie et al. 2021)

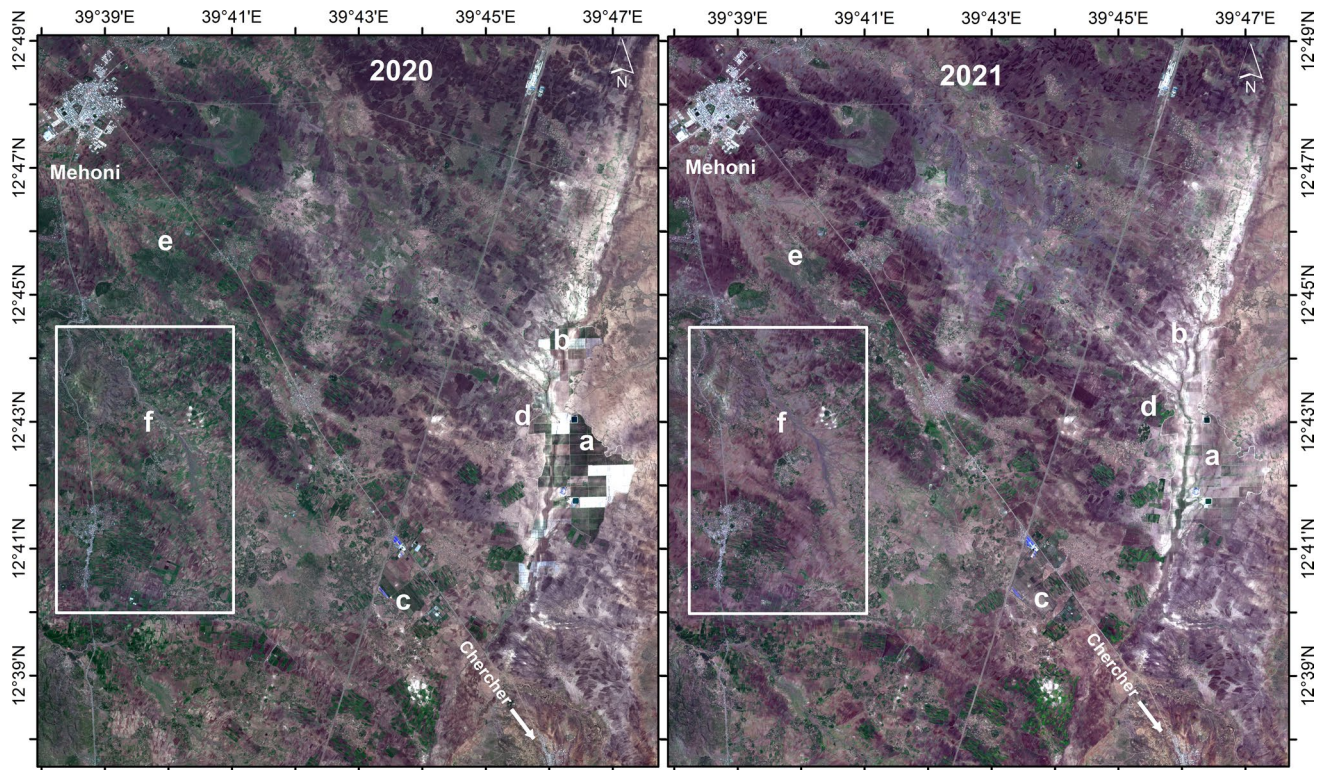


Fig. 12 Comparison of the status of irrigation and rain-fed agriculture in the spring seasons of 2020 and 2021 in Raya using Sentinel 2 imagery. The locations **a–e** show irrigation areas. They were covered with crops during the spring seasons of 2020 but not/little in 2021.

The white box area **f** shows rain-fed agriculture covered with crops in the spring season, as climate allows a second cropping season in the area

proven to be effective for analysis of information related to agriculture especially where reliable field data are unavailable and expensive (de Beurs and Henebry 2010). In this study, we assessed the impact of the conflict in Tigray on farming activities using open access Sentinel-2 imagery processed in GEE to understand whether the ploughed and fallowed areas have changed because of the conflict. For this, we contrasted Sentinel 2-derived NDVI data from pre-war year 2020 and war year 2021, with a temporal focus on the spring season. The analysis of the Sentinel-2 images and NDVI provided reliable and good ground information about ploughing conditions at high spatial resolution (Dannenberg and Kuemmerle 2010). It has been possible to easily detect and quantify the spatial pattern of ploughing conditions and growth of weeds during the spring seasons of 2020 and 2021 at a large spatial scale covering Tigray region (Kuemmerle et al. 2008). Using the Sentinel images and NDVI, we have been able to understand whether there were fallowing and their patterns during the conflict. We have also been able to distinguish the share of ploughed and fallowed land attributable to the conflict. Hence, we conclude that the open access Sentinel-2 imagery have made possible to detect ploughed and fallowed areas during conflicts at reliable spatial resolution in which field-based measurements are impossible due to inaccessibility because of war and due to large spatial coverage.

Conclusion

The conflict in Tigray started in November 2020 by the time when farmers were harvesting crops cultivated during the previous main rainy season. Unfortunately, due to the expansive and heavy war, farmers were not fully able to collect their crops. As reported in various media outlets the war has affected the farming activities of the region. The purpose of our study was to assess the effect of the conflict on farming activities in Tigray region. The study used Sentinel 2 satellite imagery to understand how the conflict has affected agricultural practices in the region. Hence, the study focused on the spring season when farmers should plough and prepare their land for cropping in the rainy summer season. The assumptions were that if farmers were able to prepare their land in the spring season, the reflectance of farmlands as would be recorded in satellite imagery should be of soil or rock outcrops without propagating greenness. On the other hand, if farmlands were fallowed due to the conflict, greenness would increase. Hence, to understand this, we analyzed a greenness index (NDVI).

From the NDVI analysis, we indicated that the spring season of 2021 shows more green coverage in farmlands as compared to the spring season of 2020. The change

in NDVI values between the two years shows that 72% of the farmlands have experienced some green vegetation growth, whereas the remaining 28% experienced a decrease in vegetation cover in 2021 as compared to 2020. The change in greenness was distributed over the whole region implying that farmlands were fallowed or were not ploughed during the spring season.

In order to check the contribution of precipitation conditions on the increase in greenness of farmlands, we analyzed the trend of rainfall in the spring seasons of 2020 and 2021. However, the rainfall condition showed a decrease in amount in the spring season of 2021 as compared to the same season in 2020. Moreover, a regression analysis showed that there is no significant correlation between changes in precipitation and changes in NDVI. Hence, precipitation conditions were not factors for the increase in green vegetation growth in farmlands. The satellite image analysis witnesses that farmlands were not ploughed during the spring season and as a result, weed growth was inevitable. As recent photos (May–August) depict, farmers started ploughing their land after June and the crop situation in August shows a delayed sowing and crop growth. Some areas with a decrease in greenness in 2021, as compared to 2020 were related to irrigation farms. Some of these farms were covered with well-grown crops in 2020, whereas in 2021 they remained fallowed. To conclude, our study shows that farmers were not able to plough and prepare their land for cropping in June and July and many farmlands remained fallow. Moreover, the use of freely available remote sensing data (Sentinel images) has been good options for recognizing the absence of ploughing in crisis times. We recommend a further study at a larger scale to investigate more details of the impact of the war on farming activities in various communities throughout Tigray.

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Declarations

Conflict of interest On behalf of all co-authors, the corresponding author states that there is no conflict of interest.

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