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Revisiting the effects of the Ethiopian land tenure reform using satellite data. A focus on agricultural productivity, climate change mitigation and adaptation

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ABSTRACT

This study examines the effects of the land registration and certification programme introduced in 1998 in the Tigray region of Ethiopia on agricultural productivity, climate change mitigation and adaptation. We use satellite-based measures of greenness and implement a difference-in-differences approach, comparing pixels on both sides of the Tigray-Amhara regional border. Results show positive and persistent effects of the programme on agricultural productivity and climate change mitigation. By examining years when adverse climate and weather events occurred, we also find evidence of increased adaptation to climate change. We show that our results are consistent with the reform enhancing farmers' tenure security and inducing an increase in the adoption of climate smart agricultural practices.

1. Introduction

Ethiopia embarked on a land tenure reform in the late 1990s that was initially rolled out in the northernmost region of the country, Tigray. The reform led to a process of land registration and certification expected to increase farm-households' tenure security and thus to enhance their incentives in undertaking long-term land related investments (Deininger and Jin, 2006; Deininger et al., 2008). At the time of the reform, the agricultural sector contributed to almost 50% of the country's GDP, compared to a current 38%, and to about 80% of its employment, compared to 70% in 2021 (World Bank, 2021). The sector relied almost exclusively on small-scale farmers, dependent on rainfall and operating in areas with sloped and often degraded land, making them highly vulnerable to adverse climate and weather events.[1]

This study investigates the impact of the Land Registration and Certification Programme (LRCP) undertaken in Tigray on agricultural productivity, climate change mitigation and adaptation. Our outcome of interest is the Normalised Difference Vegetation Index (NDVI), an indicator of plant 'greenness' widely used in the literature, which has been shown to be associated with measures of agricultural productivity and

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[1] In 1998, there were 9.6 million small-scale farmers, who farmed 95% of all agricultural land area on an average farm size of just under one hectare (FDRE, 2000; Gebre-Selassie and Bekele, 2012). The land area under irrigation represented 0.7% of total cultivated area (FDRE, 2000; Diriba, 2020; World Bank, 2006). Studies that have examined the impact of climate change in Ethiopia include Aragie (2013); Cline (2007); Deressa and Hassan (2009); FDRE (2015); Mideksa (2010); World Bank (2008); World Bank (2010); You and Ringler (2010).

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climate change mitigation.[2] Using remotely sensed satellite data, we construct a panel dataset, where 9 km by 9 km pixels are our cross-sectional units covering the regions of Tigray and Amhara, over the period 1991–2004. Our empirical approach compares pixels in Tigray, where the LRCP was first implemented, with those in the neighbouring Amhara region, before and after the implementation of the reform, within a difference-in-differences (DiD) framework. We provide tests for the absence of pre-trends and follow the latest developments in the DiD literature to appropriately deal with the inclusion of relevant covariates (Roth et al., 2022).

Before estimating the effects of the reform, we provide formal empirical tests that validate the use of NDVI as a measure of agricultural productivity and carbon uptake in the context of our study. First, we employ an approach similar to that of Gazeaud and Stephane (2022) and show strong positive correlations between census-based agricultural productivity data and NDVI within our study area.[3] Second, we show significant positive correlations between Net Primary Productivity (NPP), obtained from two separate sources, and NDVI,[4] confirming NDVI's potential use as a metric of carbon uptake over the study area.

Our study finds that the LRCP has led to increases in NDVI and the effects are persistent, suggesting a positive effect on agricultural productivity and climate change mitigation over the landscapes of Tigray. By examining years where adverse climate and weather events occurred, we also find suggestive evidence that the LRCP enhanced climate change adaptation, thereby reducing farm-households' vulnerability to such adverse events. By restricting our analysis to pixels closer to the border between the two regions, and by testing for systematic differences in weather conditions over time, we are able to exclude the possibility that the effects are driven by confounders.

This study complements existing research on the effects of the Ethiopian land tenure reform and contributes to the literature in three fundamental ways.[5] First, this study complements previous research by analysing the effects of the LRCP not only on agricultural productivity, but also on climate change mitigation and adaptation. Second, it exploits an original source of data. It is, to the best of our knowledge, the first study that utilises remote sensing data to analyse the effects of the LRCP in Tigray. In particular, and as further described in Section 4, we have acquired data over the defined areas of interest (Tigray and Amhara) for the time period ranging from 1991 to 2004 from a range of datasets publicly accessible on the Google Earth Engine platform (Gorelick et al., 2017) and have computed and exported, for each pixel in the areas of interest, relevant monthly statistics for each variable of interest, resulting in the production of an original balanced panel dataset with data for 1,008 pixels as cross-sectional units over a time period of 14 years. Third, this study extends the geographic coverage of the analysis compared to existing literature on the effects of the LRCP in Tigray. Unlike previous research, which was constrained to be localised and thus did not have external validity beyond the specific communities studied (due to the non-regional representativity of the household surveys employed), the use of remote sensing data enables us to undertake an analysis over the entire landscapes of the Tigray region and to report results that are indeed valid at the level of the entire Tigray region.[6]

2. Background on the land registration and certification programme

The Ethiopian revolution of 1974 led to the end of the Empire of Ethiopia and to the instauration of the socialist *Derg* regime, which carried out a radical land reform, seizing all rural land - without payment of compensation - and redistributing it to farmers willing to personally cultivate the land (PMAC, 1975: article 4; Cheru et al., 2019).[7] The continuous land redistributions that occurred in the years following the revolution, and the hindrance of private sector initiatives increased tenure insecurity and hampered agricultural productivity growth (Belete et al., 1991; Bruce et al., 1994; EEA/EEPRI, 2002; Rahmato, 1984). After the fall of the *Derg* regime in 1991, a new constitution was adopted in 1995. With the new constitution, land ownership remained exclusively vested in the State. However, the administration of land and of other natural resources was devolved to regional governments, which were invited to enact regional land administration laws (FDRE, 1995; 1997).

Tigray was the first region to pass such a proclamation in 1997 specifying the rights and obligations of populations with respect to land. The proclamation confirmed the impossibility of land sales and of indefinite land leases. However, and despite the absence of freehold tenure, the regional law specified that individual holdings could be leased-out (or leased-in) to (or from) other farmers (for a period of up to 10 years) (TNRS, 1997: articles 7; 9), thus opening-up a space for land market transactions that had been absent under the *Derg* regime. Furthermore, the legislation gave farm-households perpetual use rights to land as it indicated that, beyond farmers' rights to use the land in their possession until their death, the land could be given in inheritance to female and male children insofar as these were not "self-subsistent outside [the] agriculture sector" (TNRS, 1997: articles 3; 9; 16). The proclamation also included an article related to land expropriation, which indicated that land under private possession could only be taken by the State against the payment of fair compensation or the provision of similar land (TNRS, 1997: article 11). These latter two provisions were thus expected to reduce the perception of tenure insecurity that

[2] The NDVI, first introduced by Rouse et al. (1974), Rouse et al. (1973), is computed by normalising the difference between the near-infrared (NIR) and the red bands of a scene (the formula for the calculation of NDVI is therefore: (NIR - Red) / (NIR + Red)). A healthy green plant is characterised by high absorption of solar radiation by the chlorophyll in the visible red wavelength and by high reflectance by the plant's spongy mesophyll in the near-infrared wavelength (Jensen, 2014). Values of the red and NIR bands correspond to ratios between the reflected and the incoming radiation for each band and thus lie between zero and one. Therefore, values of NDVI range between minus one and plus one, with higher values representing more 'greenness' compared to lower values (Pettorelli, 2013). Further details on the literature supporting the association between NDVI and measures of agricultural productivity and carbon uptake are provided in Appendix B. For applications see: Asher and Novosad (2020); Gazeaud and Stephane (2022); GEF (2016); Groten (1993); Higgins et al. (2015); Lewis et al. (1998); Meshesha and Abeje (2018); Mkhabela et al. (2005); Sha et al. (2022); Sims et al. (2021); Tucker et al. (1980); (1986); Vlek et al. (2010); Yengoh et al. (2015).

[3] The agricultural productivity data was sourced from the 2001 Ethiopian Agricultural Census (FDRE, 2003), which is publicly accessible in the International Household Survey Network Catalog (https://catalog.ihsn.org/).

[4] As further detailed in Appendix B, NPP corresponds to the net amount of carbon assimilated by plants after photosynthesis and autotrophic respiration and can thus be considered a direct indicator of carbon sequestration from vegetation (UNCCD, 2017; Sha et al., 2022). The two sources of NPP data that we use in the regressions are FAO (2020) and Running et al. (2015). Unfortunately, neither of these two datasets covers the entire timeframe of our study, and no other publicly available dataset includes longer time-series of NPP data. We are therefore constrained by data availability to employ NDVI as a proxy of primary productivity, rather than utilising directly NPP values in our main analysis.

[5] Ayele and Elias (2018) provide a recent review of the existing literature assessing the effects of the programme across Ethiopia on various rural development objectives. We also included at the bottom of Section 2 a summary of the literature specifically related to the LRCP in the Tigray region.

[6] In addition, although a few of the existing studies that have used survey data to study the effects of the LRCP in Tigray could exploit panel data (e.g. Holden and Ghebru (2013); Holden et al. (2009); IFPRI (2013); Mekonnen et al. (2013)), the panel they used only contained a single snapshot of the pre-LRCP period, while we can observe annual progress before and after the reform.

[7] Inspired by the Soviet Union model, State and collective farms were also created by the regime.

prevailed under the *Derg* regime (Holden et al., 2009). Other regions followed suit and issued proclamations related to land administration and land use (ANRS, 2000; ONRS, 2002; SNNPRS, 2003).

After the proclamations were issued, a gradual process of land registration and certification was undertaken by regional governments. The process began in Tigray where an LRCP was implemented in 1998. Reportedly, by 1999, 88% of all land was registered and certified (Deininger et al., 2006; USAID, 2016). Amongst the positive lessons learned from the execution of the LRCP in Tigray was the localised level of administration and implementation of the programme and the communities' participation in the process (Haile et al., 2005). This enabled the registration process to be widely known to, and accepted by, the farm-households. Many of the communities' farm-household members actively participated in the formal process of demarcation of land, which was done using simple technology (e.g. with physical ropes), validated by the neighbours of the demarcated plots and recorded in paper forms that were maintained at local administration offices (Bezu and Holden, 2014).[8]

Indeed, the transparent and participatory land demarcation, registration and certification process, backed by legislation granting farm-households perpetual use rights to land, protection against eviction and partial transfer rights (through leasing), was expected to enhance farm-households' tenure security and their incentives in undertaking long-term land related investments (Deininger and Jin, 2006; Deininger et al., 2008; Holden et al., 2011a; 2011b).

In terms of the impact of the LRCP, several studies have been conducted to assess the effects of the programme in the Tigray region on a range of rural development objectives that can be associated with economic, social, and political outcomes. In the following paragraphs we provide a summary of the key findings of the existing literature.[9]

A large body of evidence suggests that the LRCP was indeed successful in reducing tenure insecurity. Holden et al. (2011a), for example, use data collected from interviews with 400 conflict mediators across 27 villages of Tigray.[10] Among the main findings of the study, the authors report that the LRCP successfully reduced the number of border disputes in many communities (Holden et al., 2011a: 27). This finding hints towards the effectiveness of the Tigray LRCP in increasing tenure security of farm-households, as land disputes and conflicts can be interpreted as a signal of tenure insecurity. The positive effect of the LRCP on tenure security has also been found in Holden et al. (2011b), who deduct from the results of land rental models and from direct information on household perceptions that an increase in tenure security occurred in Tigray following the LRCP. Similar positive effects of the LRCP on tenure security are reported by Holden et al. (2009) for a large majority of farm-households across the sampled areas of Tigray.

Positive effects are also found in terms of investment and productivity. Holden et al. (2009), for instance, employing a panel dataset based on an initial sample of 400 households, find that the LRCP led to increased investment on maintenance and improvement of soil conservation structures and on tree planting. They also find large positive and significant effects of the LRCP on total value of output per hectare across the majority of their specifications (21 out of 32). Results are confirmed in Mekonnen et al. (2013) who show an increase in tree growing in Tigray. Additional evidence on the positive impact of the LRCP on productivity is provided by Holden and Ghebru (2013), who employ the same dataset as Holden et al. (2009) but add a gender dimension in their study finding that post-certification productivity gains on land rented out by female-headed households were larger compared to that of male-headed households. Positive investment and productivity effects are also found by Ghebru and Holden (2015), based on a sample of 320 farm-households. In addition to an increase in investment in new, and maintenance of, conservation structures, they find greater use of fertilisers and of improved seed varieties. Hence, they are able to attribute the increase in productivity to the technological advantages induced by the programme (Ghebru and Holden, 2015: 25).

Few other studies have explored wider welfare effects. Holden and Ghebru (2013), for example, examine the effects of the LRCP on household expenditure per adult equivalent as a measure of welfare and find positive welfare improvements, particularly for female-headed households.[11] A study by IFPRI (2013) explores the effects on two measures of food security, calorie availability and body mass index, finding positive effects on both of these measures.

In sum, the available evidence hints towards a consensus among scholars on the beneficial effects of the LRCP in terms of tenure security, long-term land-related investments with climate-smart potential and agricultural productivity. However, none of the studies described above employed data representative at the regional level and, although a few of these could exploit panel data, the panel they used only contained a single snapshot of the pre-LRCP period. In addition, there is no direct evidence of the effect of the LRCP in terms of climate change adaptation and mitigation. Hence, our study complements the above findings by employing an original balanced panel dataset spanning from 1991 (i.e. seven years before the launch of the LRCP) to 2004 (i.e. six years after the LRCP), and covering the entire region of Tigray, to investigate the effects of the LRCP on the three CSA objectives, agricultural productivity, climate change adaptation and mitigation.

3. Conceptual framework

To uncover the impact pathway between the LRCP and agricultural productivity, climate change adaptation and mitigation, we employ, as a conceptual basis, the "Climate Smart Land Reform" (CSLR) framework introduced in Rampa et al. (2020). Because the LRCP implemented in Tigray at the end of the 1990s was a land tenure reform that was not accompanied by land redistributions, we only consider the channels linking the tenure reform pillar of the CSLR framework to the three CSA objectives, agricultural productivity, climate change adaptation and mitigation (Figure 1).[12]

The first channel depicted in Figure 1 associates tenure reform with tenure security. In fact, land tenure reforms are generally undertaken to enhance the land rights of populations and increase their tenure security (Adams, 2000). Whilst there have been circumstances where the implementation of a tenure reform did not generate the expected

[8] For a detailed description of the land registration and certification process in Tigray see e.g. Nega and Atakilt (2006); Haile et al. (2005).

[9] A description of the programme and its impact across various regions of Ethiopia, including Tigray, can be found in Deininger et al. (2008). A more recent review of the effects of the programme across Ethiopia can be found in Ayele and Elias (2018). Additional studies that have examined the impact of the programme in regions other than Tigray include Bezabih et al. (2016); Bezu and Holden (2014); Fors et al. (2019); Legesse et al. (2018); Melesse and Bulte (2015); Tsegaye et al. (2012).

[10] Administratively, Ethiopia is sub-divided into regions, zones, districts (*woredas*) and municipalities/villages (*kebeles*). There have been considerable changes in the various administrative levels throughout Ethiopia's history (most recently, the number of regions in Ethiopia increased from nine to ten with the secession of Sidama region from the Southern Nations Nationalities and Peoples (SNNP) region following a referendum in late 2019). At the time of the latest population census (2007), Ethiopia was subdivided in nine regional states (and two administration cities), 73 zones, 731 *woredas*, and 16,328 *kebeles* (Central Statistical Authority, 2012).

[11] For a more in-depth assessment of gender-focused effects of the land tenure reform in Ethiopia the reader may refer to Holden (2020).

[12] For the original illustration depicting the CSLR framework see Rampa et al. (2020). The importance of the other two pillars of the framework (i.e. rural advisory services and markets and infrastructure) in fostering CSA adoption and the realisation of the CSA objectives should not be neglected. Due to data limitations, we do not examine these in this study and leave such an analysis for future work.

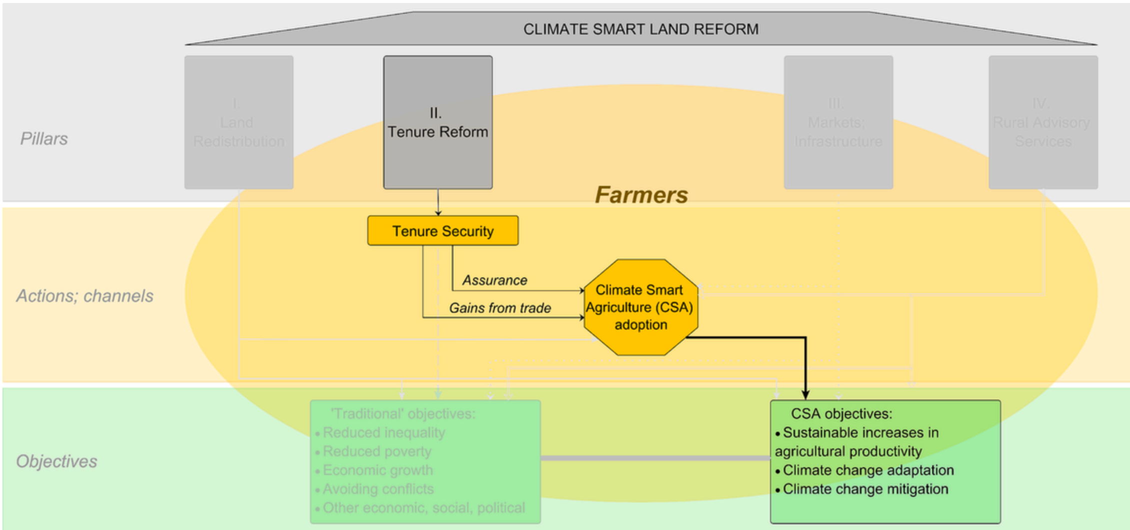

Figure 1. Tenure reform and Climate Smart Agriculture in Ethiopia.
Source: Authors, based on Rampa et al. (2020)..

increase in tenure security (Bruce and Migot-Adholla, 1994; Deininger and Feder, 2009; Jansen and Roquas, 1998; Pinckney and Kimuyu, 1994), the empirical evidence available from the LRCP implemented in Tigray suggests that, despite the absence of a freehold tenure system, the reform was indeed successful at enhancing farm-households' tenure security (Holden et al., 2009; 2011a; 2011b). The land certificates received by farm-households in Tigray embodied perpetual use rights, protection from expropriation, and partial transfer rights to a land that had been demarcated and registered following a transparent and participatory process. Hence, the LRCP enhanced tenure security by reducing the risk of arbitrary evictions (without fair compensation) and of land encroachment (Holden et al., 2009; 2011a).

In turn, increased tenure security amplifies farm-households' incentives to undertake long-term land related investments, including investments in the adoption of practices with climate-smart potential (intermediate channel in Figure 1). In the Ethiopian context, two forces are considered to underlie such incentives.[13] The first is the *assurance* effect. With greater tenure security, farmers gain confidence that the returns from undertaking investments on the land, including in CSA practices, will not be reaped by outsiders but will instead be garnered by them and their heirs. Expected returns from these investments will thus be higher, which will create a stimulus for these investments to be realised (Besley, 1995; Brasselle et al., 2002; McCarthy and Brubaker, 2014). The second effect is associated with potential *gains from trade* from investing in CSA practices.[14] Two conditions are subsumed in this effect. First, a land market must exist where increased tenure security reduces transaction costs. In the context of Ethiopia, where only land leases are permitted, higher tenure security is expected to reduce the lessor's potential costs of losing their rights to the land.[15] Second, the land market must recognise the value of climate-smart investments undertaken on the land (e.g. the value of terraced land must be greater than the value of non-terraced land).[16] If these conditions are met, farm-households will have an incentive to invest in CSA as they will be able to gain a return from these investments when leasing out their land.[17]

The last channel highlighted in Figure 1 links CSA adoption with agricultural productivity, climate change adaptation and mitigation (i.e. the three CSA objectives). This channel is depicted in bold in the figure as, by definition, adoption of CSA is expected to generate improvements in terms of the CSA objectives (FAO, 2017).

To conclude, the conceptual basis of our study relies upon the effect that the LRCP has on enhancing tenure security for farm-households and the consequent assurance and gains from trade (leasing) effects. The combination of these effects is expected to provide incentives for farm-households to invest in long-term land related CSA practices and thus to generate beneficial effects on agricultural productivity, climate change adaptation and mitigation.

4. Study area and data

Our study focuses on two specific areas of Ethiopia, the Tigray region (where the LRCP was first implemented – the "treated" region) and the Northern part of Amhara (the "control" region). While the Amhara region has a total land surface that is over three times that of Tigray, we only include in our analysis a selected area of Amhara, similar in size to Tigray (Figure 2, panel a).[18] This also allows us to ensure that agro-ecological characteristics are not excessively dissimilar between the two study regions. The four panels included in Figure 2 show that when considering crucial factors associated with agricultural production such as the agro-ecological zoning, the total amount of annual rainfall and the

[13] The literature highlights other positive effects that may emerge with the implementation of a tenure reform (Feder, 1987; deSoto, 2000; Dixon-Gough and Bloch, 2006; McCarthy and Brubaker, 2014; Rampa et al., 2020). Among these, the most prominent is arguably the *collateralisation* effect, which is impeded in the Ethiopian context by the absence of household ownership rights to land, as all land is vested in the State.

[14] This effect, which is termed here *gains from trade* following Besley (1995), is also referred to as *realisability* effect or *transferability* effect in the literature (Brasselle et al., 2002; McCarthy and Brubaker, 2014).

[15] In Ethiopia land sales remain prohibited after the tenure reform - land market activity can only occur by means of land leases between farm-households (FDRE, 1997; TNRS, 1997).

[16] For a formal model of the gains from trade effect detailing the conditions that ensure a successful bargaining process, see, for instance, Besley (1995: 910-912).

[17] In a similar vein, increased land market activity can also generate allocative efficiency gains, by reallocating land from less productive to more productive farmers (Holden and Ghebru, 2013).

[18] In addition, a buffer of five kilometres from the Tigray and Amhara borders is excluded to avoid pixel contamination (i.e. to avoid utilising in the analysis pixels with portions of land not within the areas of interest), and a land cover mask is applied based on the European Space Agency's global land cover product to remove pixels classified as "built-up" (i.e. urban areas), "bare/sparse vegetation", and "permanent water bodies" (Zanaga et al., 2021) In total, we obtain 1,008 pixels, 504 pixels representing the Tigray region and 504 pixels representing the corresponding area of Amhara.

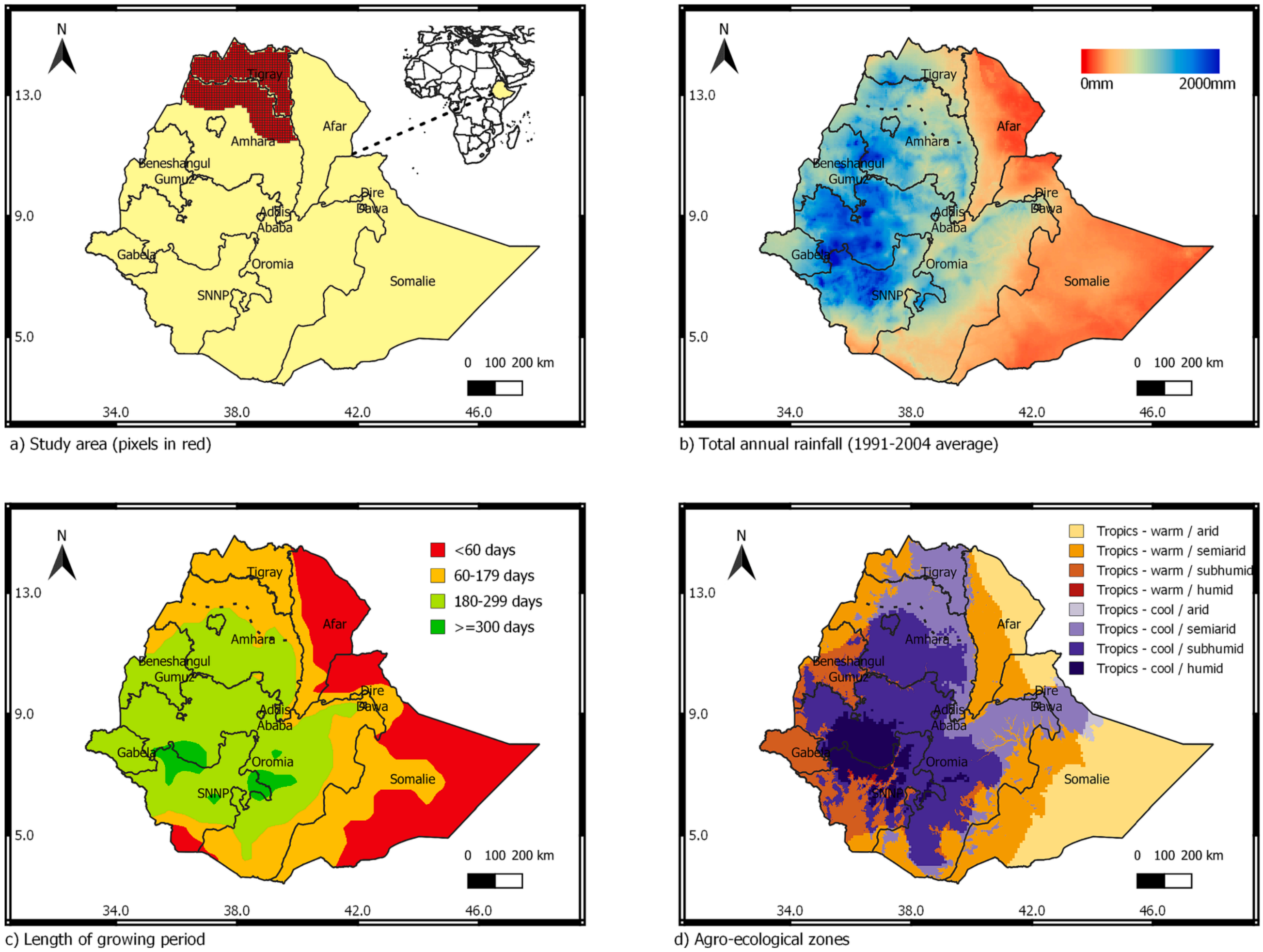

Figure 2. Characteristics of the study area.
Sources: Authors, based on the following data: for total annual rainfall, (Funk et al., 2015a); for length of growing period, Fischer et al. (2002); for agroecological zones, Sebastian (2009).

length of growing period, the study area is indeed more homogenous compared to a possible alternative area containing the entirety of the Amhara region. Furthermore, restricting our study area to the northernmost part of Amhara enables us to exclude areas of Amhara that were selected in the pilot LRCP launched in 2003, namely Gozamen in East Gojam zone, and Dessie Zuria in South Wollo zone (Adenew and Abdi, 2005: 13) and thus to extend the timeframe of the analysis until 2004, when the Amhara land administration authority began expanding the LRCP across the region.[19]

We rely on remote sensing data sourced from the Google Earth Engine platform (Gorelick et al., 2017). Our main variable of interest is the monthly maximum value of the Normalised Difference Vegetation Index (NDVI). As indicated above, NDVI is a measure of plant 'greenness' that has been shown in the literature to be associated with measures of agricultural productivity and climate change mitigation.[20] Various raw and processed satellite data can be employed to obtain NDVI values, in our study, we recur to the AVHRR NDVI third generation (3 g) dataset (Pinzon and Tucker, 2014), which not only corrects for a number of potential distortions caused by navigation inaccuracy, stratospheric aerosols, orbital drifts, cloud presence (Tucker et al., 2005) but also for potential biases induced by the use of multiple sensors (Pinzon and Tucker, 2014).[21] AVHRR NDVI 3 g has the advantage over other datasets of including a long time-series of bi-monthly, consistent and global NDVI data. These strengths make it a very widely used dataset in the literature (Davis et al., 2017; Lamchin et al., 2018; Pettorelli, 2013; Zhou et al., 2018). Crucially, the AVHRR NDVI 3 g dataset is the only dataset available that provides reliable NDVI data over the entire timeframe of

[19] It was not possible to ascertain the precise dates at which the LRCP was undertaken in the areas of interest of Amhara. This is due to a lack of information available, as reported in Deininger et al. (2008) "In fact, as responsibility is fully with the regions, even information on implementation of certification available at the central level is often quite inaccurate" (Deininger et al., 2008: 1808). However, based on available information, the year 2004 appears to be a conservative estimate, particularly with regards to the certification facet of the programme in the study areas of Amhara: "The first round […] was fielded in 2004 when, except for Tigray and some small local pilots, no land certification had been undertaken anywhere in the country" (Deininger et al., 2008: 1790); "in Amhara […] At the end of 2004, about 30% of farming household plots were registered" (Kanji et al., 2005: 12); "By the end of 2004, about 660,687 landholders received temporary certificates [… and] 3.6 million plots were registered"(Adenew and Abdi, 2005: 18). Combining the information from these latter two reports, we can estimate that at the end of 2004 approx. 20 percent of landholders in Amhara had received certificates.

[20] One drawback of the NDVI is that it suffers from saturation at very low and very high index values. However, this is not a concern in the context of this study as the index values over the areas of interest are not extreme.

[21] The dataset relies on the National Aeronautics and Space Administration (NASA)/National Oceanic and Atmospheric Administration (NOAA) instruments and is processed by the Global Inventory Modelling and Mapping Studies (GIMMS) group.

this study.[22]

Additional variables of interest for our study include measures of precipitation, temperature and wind speed - which are considered to potentially affect NDVI - as well as an index enabling us to capture adverse climate and weather events.

Historical precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data, a quasi-global rainfall dataset, that incorporates satellite imagery with in-situ station data (Funk et al., 2015a). This dataset has been validated over Eastern Africa (Dinku et al., 2018) and, more specifically, over areas of Ethiopia (Funk et al., 2015b; Ayehu et al., 2018; Alemu and Bawoke, 2020; Alemu and Wimberly, 2020). Due to its reliability, the CHIRPS dataset is increasingly being employed in the literature, including in studies relating to Ethiopia (Osgood et al., 2018; Taye et al., 2018; IPCC, 2019). As the monthly data product was not available on the GEE platform, we recurred to the pentad dataset (consisting of five-day sums of precipitation) and subsequently computed the arithmetic monthly sum from the pentad data for each pixel.

For temperature data, we employ the Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) dataset (McNally et al., 2017), which provides monthly average "near surface air temperature".[23] This dataset has a good track record in terms of accuracy, including in areas of Ethiopia. Alemu and Wimberly (2020) study various satellite-based remote sensing temperature and precipitation datasets and compare values from these datasets to those obtained from 22 meteorological stations across the Amhara region of Ethiopia. They find that, amongst the datasets studied, the FLDAS temperature data and the CHIRPS precipitation data were the most closely related to station data.

Average monthly wind speed data were obtained from the TerraClimate dataset, a global long time-series dataset (1958-current) which includes a range of primary climate variables as well as variables derived from a soil water balance model (Abatzoglou et al., 2018). Although the TerraClimate dataset was only released in 2018, it has already been employed extensively in empirical research. Data relating to wind speed from the TerraClimate dataset have been utilised for instance by Gudo et al. (2020); Hu et al. (2020) and by Fenta et al. (2020) in the context of Ethiopia.

The Palmer Drought Severity Index (PDSI) is a widely used index for the objective classification of adverse climate and weather events according to a severity scale. It was originally developed as a tool to allow comparisons across time and space of meteorological drought episodes (Palmer, 1965). Yet, the index includes both negative and positive values and can therefore be employed to determine not only dry spells but also abnormal wet periods. The computation of the index is based on a soil moisture algorithm and a water balance model, which produce values that can be categorised according to a scale of severity (Palmer, 1965). The values of PDSI utilised in this paper were obtained directly from the TerraClimate dataset. The PDSI has been used extensively in research, including in Ethiopia (Asfaw et al., 2018; Temam et al., 2019). In our study, and as further described below, we employ the PDSI as a measure to identify adverse climate and weather events that occurred during the timeframe of the study and that represented a potential threat to agricultural production systems.

A balanced panel dataset was constructed from these data utilising monthly time intervals ranging from 1991 to 2004 and 1,008 pixels of approximately 9 km $\times$ 9 km as cross-sectional units, half of which correspond to the geographic area of Tigray and half to a similar-size area in the neighbouring Amhara region. This resulted in a total of 169,344 observations. Detailed summary statistics are shown in Appendix Table A1.

5. Empirical approach

One of the advantages of recurring to remote sensing satellite data is the possibility of generating (balanced) panel datasets by obtaining comparable time-series data over a refined level of analysis (pixels). Our empirical strategy is based on a difference-in-differences (DiD) approach, with one treatment period, that compares pixels on both sides of the Tigray-Amhara regional border before and after the 1998 LRCP. Therefore, this design corresponds to a simple two-period (pre-treatment and post-treatment) and two-group setting, where the LRCP represents the treatment, and pixels in Tigray form part of the treatment group, whilst pixels in the selected area of Amhara represent the control group (which is never-treated during the timeframe of our study). Formally, we estimate the following equation:

$$NDVI_{irt} = \beta(D)_{irt} + \zeta x_{irt} + u_i + v_t + \varepsilon_{irt} \quad (1)$$

where i indicates a pixel in region r (Tigray or Amhara) in month-year t. D is a dummy variable equal to one for pixels in the treated region (Tigray) and for years following the 1998 LRCP, and equal to zero otherwise. x is a vector of pixel-and-time-varying covariates, u is a vector of pixel fixed effects and v a vector of time fixed effects.[24] The coefficient of primary interest is β, which provides an estimate of the average treatment effect on the treated (ATT). The dependent variable NDVI is our satellite-based measure of greenness. Finally, ε is the error term clustered at *woreda* level; there are 71 clusters in our analysis.[25] We estimate the above model using ordinary least squares (OLS) and also implement the Doubly Robust (DR) estimator proposed by Sant'Anna and Zhao (2020). This latter estimator combines the outcome regression approach (Heckman et al., 1997) and the propensity score weighting approach (Abadie, 2005) to estimate the causal effect of the treatment, conditional on covariates, without requiring additional homogeneity

[22] Other sources include the collections from the Moderate Resolution Imaging Spectroradiometer (MODIS), or Landsat (see, for instance, Higginbottom and Symeonakis, 2014; Pettorelli, 2013 for summaries of commonly utilised NDVI datasets) and more recently from the European Space Agency's Copernicus Sentinel missions (Aschbacher and Milagro-Pérez, 2012). Although Landsat, MODIS and Sentinel data provide a finer spatial resolution compared to AVHRR NDVI 3g, we consider the above-stated advantages of this latter dataset to outweigh the benefits of higher spatial resolution, particularly given the regional-scale of the analysis that we undertake. In fact, the long time-series and consistency of AVHRR NDVI 3g data enable us to obtain a balanced panel dataset ranging from 1991 to 2004 over the study area. MODIS and Sentinel data are only available from the years 2000 and 2015, respectively, therefore from only after the implementation of the LRCP in Tigray, and large gaps were found in Landsat data for substantial time periods over the areas of interest. None of these alternative datasets were thus available for the entire timeframe of our study.

[23] Temperature data in the FLDAS dataset is based on NASA's Modern Era Reanalysis for Research and Applications version 2 (MERRA-2) (Bosilovich et al., 2015).

[24] While farmers in Tigray could have received the certificates at different points in time, the process was considered to have been setup and performed very quickly (Deininger et al., 2006). The LRCP started in 1998 and, by 1999, 88% of rural households in Tigray had received a certificate. Hence, most of the staggering would have occurred within a short period of time. For the remaining 12%, we do not have information on which households were reached last, yet late certifications are unlikely to be driven by spatial conditions. Deininger et al. (2006) suggest that delays are likely caused by households not being present in person or because of disputes, rather than because of location-specific conditions.

[25] This approach is also referred to as Two-Way Fixed Effects (TWFE) in the literature, due to the inclusion of both unit and time fixed effects. In a two-period and two-group setting, with only one treatment period and one treated group, TWFE estimates have been shown to produce unbiased ATT even in the presence of dynamic treatment effects (Baker et al., 2022).

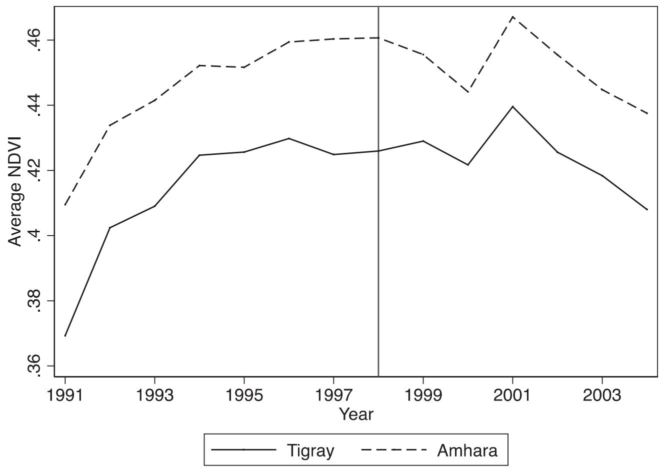

Figure 3. NDVI values for treated and control areas (1991–2004).
Notes: NDVI values are annual averages over the treated (solid lines) and control (dashed lines) areas, and are obtained from the dataset constructed based on AVHRR NDVI 3 g data (Pinzon and Tucker, 2014).

assumptions (Sant'Anna & Zhao, 2020).[26]

The results from the estimation of equation (1) are intended to guide inference on whether the LRCP in Tigray contributed to increases in agricultural productivity and to climate change mitigation. In order to study the effects of the tenure reform on the second CSA objective (i.e. climate change adaptation), we restrict our dataset to include only years where adverse climate and weather events occurred and apply equation (1) to this sub-set of the dataset. The intuition is the following. If the land tenure reform provided thrust to enhance land related investments in Tigray, which in turn helped build resilience to the adverse effects of climate change, then the ATT from the estimation of equation (1) with this sub-dataset should be positive. In other words, a positive ATT in the presence of adverse climate and weather events should be indicative of increased adaptation to climate change. To identify the years when such adverse events occurred, we employ the monthly PDSI values for each pixel and compute the *kiremt* season PDSI average for each year.[27] Following the original PDSI classification (Palmer, 1965), we include in the sub-dataset the years where the *kiremt* season PDSI average is either below minus one (i.e. "mild drought" conditions or worse) or above one (i.e. "slightly wet" conditions or worse).

5.1. Identification

The causal interpretation of our estimated ATT relies on the assumption that, in the absence of the reform, pixels in the two regions would have experienced similar trends in greenness (known as parallel trends assumption). This assumption cannot be directly tested. Yet, we can provide some support for this assumption by confirming the absence of pre-treatment differences in trends between the two regions. We do so, first, through a visual inspection of the raw annual averages of NDVI over Tigray and Amhara, which are plotted in Figure 3. These raw averages show that trends in NDVI in both regions are broadly aligned in the pre-treatment period, providing descriptive support for the absence of differences in pre-treatment trends. Second, we adopt an event-study approach that includes leads and lags of the treatment:

$$NDVI_{irt} = \sum_{\tau=-q}^{-1} \delta_\tau T_{ir} + \sum_{\tau=0}^{m} \theta_\tau T_{ir} + \zeta x_{irt} + u_i + v_t + \varepsilon_{irt} \quad (2)$$

Where δ_τ and θ_τ correspond to the coefficients of the leads and lags of the treatment T, respectively, and all other terms are as in equation (1). Another advantage of equation (2) is that it allows for treatment estimates to vary over time, and so it offers the possibility to observe post-treatment coefficients and investigate the persistence of the estimated effects.[28]

Besides differences in pre-treatment trends, we are also concerned about pre-treatment differences in the level of NDVI as the underlying causes of such differences could potentially influence post-treatment trends. In fact, we can see in Figure 3 that Tigray displays lower levels of NDVI, on average, compared to Amhara during the pre-treatment period.[29]

We employ two different approaches to address these differences. First, we conduct the analysis by restricting pixels in both treated and control group to areas that fall within 75 km and 50 km from the Tigray-Amhara border (Figure 4 panels a and b, respectively).[30] While we are unable to implement a proper regression discontinuity design due to lack of power at the cut-off, as we restrict the sample to pixels closer to the regional border, the pre-treatment differences in NDVI levels shrink significantly. Analysing pixels that are closer to the regional border has two additional advantages. First, and as further described below, it allows us to compare areas with increasingly similar weather conditions. Second, it enables us to exclude the northernmost areas of Tigray, which might have been affected by the 1998–2000 conflict with Eritrea. As a second approach, we use two matching-based techniques to form the counterfactual. In particular, we use propensity score matching to match pixels in Tigray to similar pixels in Amhara based on annual pre-treatment average NDVI. Figure 4 (panel c) shows average NDVI for pixels in the common support, while panel d) shows weighted averages where weights are given by the occurrences of pixels in the control group, after we impose a common support in the propensity score (Heckman et al., 1998).[31] In both cases, differences in pre-treatment means nearly disappear rendering pre-treatment trends and levels close to identical.

Time-varying factors correlated with the treatment could still challenge the validity of our results. Weather conditions, for instance, could diverge between Tigray and Amhara over the period of analysis and influence post-treatment differences in trends. We therefore check for systematic differences in weather conditions between the two regions, before and after the reform, using an event study where the outcome

[26] The additional assumptions would be: homogenous treatment effects (i.e. weather conditions affect NDVI in the same direction and magnitude before and after the reform) and no-covariate specific trends in both the treatment and control group.

[27] As illustrated in Appendix Figure A, the *kiremt* season (June to September) corresponds to the rainy season in our study area. Farm-households rely on the *kiremt* rains for their agricultural production, and rainfall anomalies during the *kiremt* season can impact farm harvest, total agricultural output and consequently the livelihoods and food security of farm-household members.

[28] Investigating the persistence of the estimated effects throughout the post-treatment period is particularly relevant to gauge whether the LRCP contributed to progress in terms of one of the CSA objectives, namely 'sustainable increases in agricultural productivity' (FAO, 2017). In effect, sustaining higher levels of agricultural productivity through time (i.e. beyond one single season) can be indicative of sustainable increases in productivity.

[29] We are not concerned with possible self-selection (i.e. whether pixels with lower level of NDVI were more likely to be selected into the programme) as all pixels in the Tigray region are considered treated by the reform. Instead, we are concerned about the possibility that any factor that led to the pre-treatment differences in NDVI levels could also lead to post-treatment differences in trends.

[30] Data exclude the five km buffer from the Tigray border to avoid cross-border pixel contamination, as specified in Section 4 above.

[31] The weights for pixels in the Tigray region, and in the common support, are equal to one while those for pixels in the control group are given by the number of times a pixel is matched to a counterpart in Tigray. Following Heckman et al. (1998), matching is based on propensity scores using a bandwidth for the uniform kernel of 0.06. Results from the estimation of specifications employing these alternative methods are presented in Section 6.1.1.

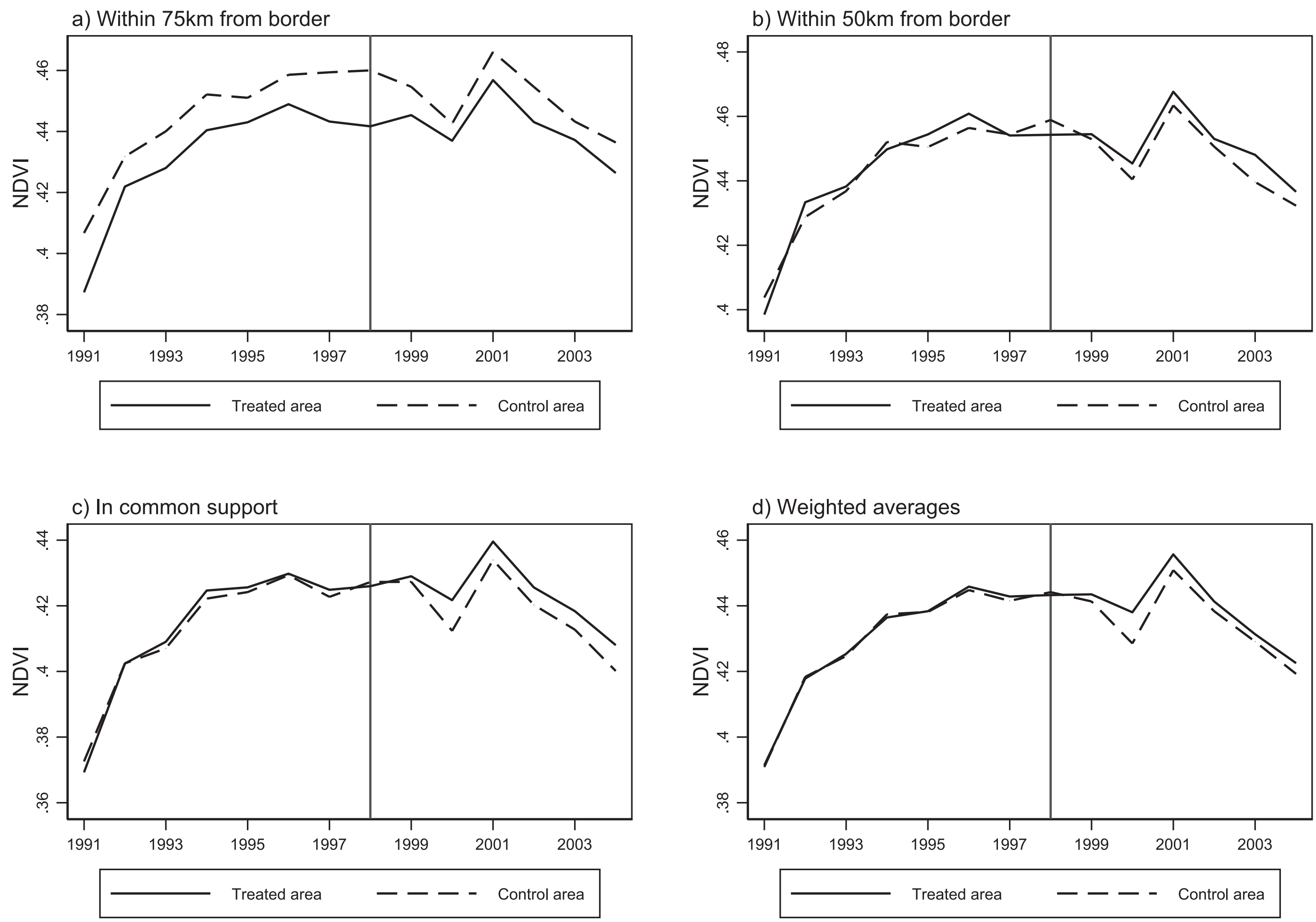

Figure 4. NDVI values for treated and control areas (1991–2004): different methods to define the counterfactual.
Notes: NDVI values are annual averages over the treated (solid lines) and control (dashed lines) areas, and are obtained from the dataset constructed based on AVHRR NDVI 3 g data (Pinzon and Tucker, 2014). Panels a) and b) are obtained by restricting the sample to pixels within 75 km and 50 km from the Tigray-Amhara regional border, respectively; panel c) shows NDVI averages only for pixels falling in the common support of a propensity score matching based on pre-reform levels of NDVI; panel d) shows weighted averages which use the occurrences of pixels in the control group, after matching on propensity scores with a bandwidth of 0.06.

variables are rainfall, temperature and wind speed.[32] We also control for these variables in our model, while also showing results when excluding individual control variables. It is worth noting that the inclusion of weather variables that might vary differently between the treated and control group does not affect our identification strategy, as such changes are driven by exogenous forces that are unrelated to the outcome and the treatment (Sant'Anna & Zhao, 2020). In addition, as suggested above, when restricting the analysis to pixels closer to the border, the possibility that treated and control pixels experience different weather patterns is substantially reduced.

We conduct three final robustness checks. First, we include *woreda*-time trends to control for localised events that could affect NDVI. Second, we employ an alternative outcome variable, the monthly average of NDVI (in place of the monthly maximum), across the entire set of specifications. Finally, we check for additional geographic-based heterogeneities that might be driving the results. In particular, we explore whether the exclusion of the westernmost areas of Tigray and Amhara, where agroecological conditions are slightly different compared to the rest of the study area (Figure 2 panel d), affects our results.

[32] The results from the event studies are presented in the Appendix (Figure B, Figure C and Figure D).

Table 1
Effects of the LRCP on NDVI: Average treatment effects on the treated (ATT).

Dependent variable: NDVI	(1) OLS	(2) OLS	(3) Doubly Robust
ATT	0.005***	0.009***	0.009***
	(0.002)	(0.002)	(0.003)
FE	Yes	Yes	Yes
Controls	No	Yes	Yes
NDVI mean (st.dev.)		0.433 (0.137)	
Observations (pixels)		169,344 (1,008)	

Notes: Standard errors are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5%, * at 10%. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables. FE: Fixed Effects. Columns (1) and (2) are estimated using OLS, whilst column (3) results from the use of the Doubly Robust estimator proposed by Sant'Anna and Zhao (2020).

6. Main results and discussion

6.1. Agricultural productivity and climate change mitigation

Table 1 shows the results obtained from the estimation of the model presented in equation (1). Columns (1) and (2) correspond to the results from specifications without and with the inclusion of the control variables described in Section 4, respectively, and are estimated using OLS.

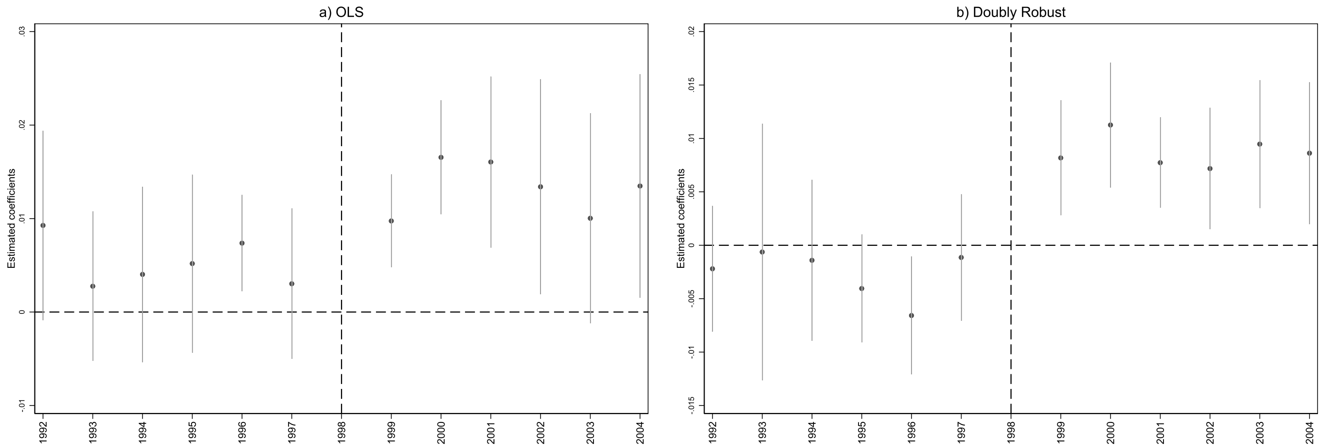

Figure 5. Average treatment effects on the treated over the study period.
Notes: The figure illustrates the results from an event study on the effect of the treatment (land registration and certification programme) on the outcome variable NDVI. Leads and lags of the treatment indicator are included in the estimated equation. Resulting coefficients are shown with 90% confidence intervals (solid vertical lines). Results are obtained using a simple TWFE estimator (Panel a) OLS) and the Doubly Robust method proposed by Sant'Anna and Zhao (2020) (Panel b) Doubly Robust).

Both columns point toward a positive and significant effect of the LRCP on NDVI. Column (3) shows that the use of the Doubly Robust estimator proposed by Sant'Anna and Zhao (2020) does not affect the sign nor magnitude of the estimated ATT.[33] The estimated average effect reported in columns (2) and (3) corresponds to 7 percent of a standard deviation (and 2.2 percent of the mean of NDVI for Tigray, the treated region). Whilst these effects may appear to be small, they should not be perceived as negligible. An indicative benchmark is provided by a 2016 independent evaluation of Global Environment Facility (GEF) projects that were aimed at combating land degradation. At the global scale, GEF projects were found to have increased NDVI by approximately 0.03 relative to an average NDVI of 0.55 (GEF, 2016: 2). The reported increases for projects in Africa appear to be smaller, with average increases in NDVI of 0.018 (GEF, 2016: 22). While our effects are smaller, it is worth considering that GEF projects were purposefully financed to reduce land degradation and improve land productivity, whilst the LRCP did not explicitly target such outcomes. Hence, the ATT from the LRCP can be considered nontrivial.

Our results rely on the validity of the main identification assumption mentioned in Section 5.1, that is the common trends assumption. In this optic, Figure 5 illustrates the results from the estimation of equation (2) using OLS and the methods proposed by Sant'Anna and Zhao (2020). In both cases, the pre-1998 estimates confirm the initial impression obtained from the visual inspection of Figure 3 and provide evidence of the absence of significant differences in pre-treatment trends between the treated and control regions.[34] The event studies also indicate that the effects of the LRCP are statistically significant in individual post-treatment years. In fact, the effect of the treatment remains present up to six years after the treatment, which suggests that the LRCP led to sustainable effects over the landscapes of Tigray.

In the context of our study, we consider NDVI to be a relevant proxy for agricultural productivity. This is demonstrated by the results in the first panel of Table 2 that show a strong correlation between NDVI and agricultural productivity data from the 2001 Agricultural Census (FDRE, 2003).[35] This is in line with the findings from Meshesha and Abeje (2018) who reported a strong correlation between NDVI and teff and wheat yields in Amhara, and from Gazeaud and Stephane (2022) who validated their use of NDVI as an indicator of agricultural productivity in Ethiopia from the significant correlation between survey-based measures of agricultural productivity and NDVI.

The results from Table 1 and from the event studies can therefore be interpreted as evidence that the LRCP had a positive effect on agricultural productivity over the landscapes of Tigray. These results are in line with previous findings from studies that employed household-and-plot-level data to analyse the impact of the LRCP on agricultural productivity in Tigray (Ghebru and Holden, 2015; Holden et al., 2009; Holden and Ghebru, 2013). However, survey-based data constrained such studies to a limited geographic and temporal coverage. The use of satellite-based data enables us to extend the spatial and temporal scale of the analysis to all rural areas of Tigray, therefore covering the close to 700 thousand agricultural households of Tigray, over a period of time ranging from 1991 to 2004.

The results from Table 1 and from the event studies can also be interpreted as suggestive evidence that the LRCP contributed positively to climate change mitigation. In effect, the NDVI as a measure of 'greenness' has been associated in the literature not only with agricultural productivity but also with net primary productivity, atmospheric carbon dioxide concentration and carbon stock (GEF, 2016; IPCC, 2019; Tucker et al., 1986; UNCCD, 2017; Vlek et al., 2010; Yengoh et al., 2015). The positive effect of the reform on climate change mitigation would have occurred due to the enhanced adoption of livelihood

[33] Based on a suggestion made by an anonymous reviewer, we have also conducted estimations when excluding the year 1999 from our post-treatment period. Results remain very much aligned with those presented in Table 1.

[34] Following Roth (2022), we carefully examined pre-treatment event study coefficients. Our results show that 1) only one pre-treatment coefficient is statistically different from zero, 2) the sum of all pre-treatment coefficients is not statistically different from zero, and 3) the estimated coefficient of the slope of the treatment effect trend line during the pre-treatment period is not statistically different from zero. These results thus strengthen the evidence of the absence of differences in pre-treatment trends and increase our confidence in the non-violation of the common trend assumption.

[35] Further results are provided in Table A 4 of the Appendix.

Table 2
Correlations between NDVI and agricultural productivity, and between NDVI and Net Primary Productivity (NPP).

	Cereals yields		NPP	
	(1)	(2)	(3)	(4)
NDVI	2.153***	2.698***	5.682***	5.933***
	(0.432)	(0.448)	(0.224)	(0.143)
Pixel FE	N.A.	N.A.	Yes	Yes
Region FE	No	Yes	Yes	Yes
Year FE	N.A.	N.A.	Yes	Yes
Observations	63	63	157,248	60,480

Notes: Columns (1) and (2) report results of the correlations between NDVI and agricultural productivity (cereal yields), with yield data obtained from the 2001 Ethiopian Agricultural Census (FDRE, 2003). Columns (3) and (4) report results of the correlations between NDVI and NPP, with NPP data sourced from the MODIS Terra dataset (Running et al., 2015) and from the FAO Water Productivity Open Access Portal (WaPOR) (FAO, 2020), respectively. Standard errors are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5%, * at 10%. FE: Fixed Effects.

Table 3
Effects of the LRCP on NDVI: Results from the main robustness checks.

	Results by distance to the Tigray-Amhara regional border		Results based on matched DiD	
	(1)	(2)	(3)	(4)
Dependent variable: NDVI	75 km from border	50 km from border	In common support	Weighting
ATT	0.008***	0.008***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Pixel FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
NDVI mean	0.442	0.445	0.417	0. 444
(st. dev.)	(0.140)	(0.140)	(0.134)	(0.138)
Observations	131,208	88,536	115,416	114,576
(pixels)	(781)	(527)	(686)	(681)

Notes: Standard errors for columns (1) and (2) are clustered at the *woreda* level, whilst for columns (3) and (4) they are block bootstrapped at the *woreda* level to account for correlated errors and the multi-step estimation procedure. *** Indicates significance at 1%, ** at 5%, * at 10%. FE: Fixed Effects. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables.

strategies with climate change mitigation potential. There is indeed evidence that, across Tigray, rural populations were adopting strategies such as tree planting on private plots (Berhe et al., 2013; EEA/EEPRI, 2002; Holden et al., 2009; ICRAF, 2019; Mekonnen et al., 2013), as well as the use of soil and water conservation practices such as conservation tillage, terracing, bunding (EEA/EEPRI, 2002; FDRE, 2003; Ghebru and Holden, 2015; Holden et al., 2009; IFPRI, 2006; Munro et al., 2008). Although most of these practices are commonly advocated for their climate change adaptation benefits, they are also effective at mitigating climate change. The high potential of such practices in reducing soil erosion, and more in general land degradation, can translate in lower carbon dioxide emissions (Altieri and Nicholls, 2017; Lal, 2003b) as well as in increased carbon sequestration (Bruce et al., 1999; Gelaw et al., 2014; Lal, 2003a; 2004; 2013; 2016; Paustian et al., 2016).[36] Indeed, several of these practices can be considered as 'optimal land management practices' that enhance NPP and contribute to climate change mitigation (Sha et al., 2022). The correlations found between NDVI and NPP over our study area (second panel of Table 2 and Appendix Table A5) provide further evidence of a positive effect of the LRCP in terms of carbon uptake. In other words, a positive and significant ATT can be considered as suggestive evidence of a positive effect of the LRCP on climate change mitigation.

Table 4
Effects of the LRCP on NDVI (climate change adaptation sub-dataset): Average treatment effects on the treated (ATT).

Dependent variable: NDVI	(1) OLS	(2) OLS	(3) Doubly Robust
ATT	0.007***	0.010***	0.009***
	(0.002)	(0.002)	(0.003)
FE	Yes	Yes	Yes
Controls	No	Yes	Yes
NDVI mean (st.dev.)	0.429 (0.133)		
Observations (pixels)	108,864 (1,008)		

Notes: Sub-dataset contains the years where adverse dry/wet conditions were identified, based on the PDSI data. Standard errors are clustered at the woreda level. *** Indicates significance at 1%, ** at 5%, * at 10%. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables. FE: Fixed Effects. Columns (1) and (2) are estimated using OLS, whilst column (3) results from the use of the Doubly Robust estimator proposed by Sant'Anna and Zhao (2020).

6.1.1. *Robustness*

In this section we present the results from the two approaches used to refine the study areas in order to ensure greater comparability between the treated and control units. The first two columns of Table 3 show the results when we restrict the analysis to pixels that are closer to the

[36] We provide further evidence on the adoption of certain conservation and mitigation strategies in Section 7 below.

Table 5
Correlations between NDVI and adoption of CSA practices.

Dependent variable: NDVI	(1)	(2)	(3)	(4)
Independent variable:	Proportion of holders with permanent crops	Proportion of holders' land area with permanent crops	Number of trees per holders' land area	Proportion of holders with contour ridges
Without controls	0.159***	1.498**	0.003*	0.089*
	(0.054)	(0.671)	(0.002)	(0.050)
With controls:				
Slope and altitude	0.136**	1.331**	0.003	0.102**
	(0.058)	(0.655)	(0.002)	(0.048)
Slope, altitude and temperature	0.197***	1.655**	0.004**	0.071
	(0.055)	(0.612)	(0.002)	(0.043)
Slope, altitude, temperature, rainfall	0.149***	1.464***	0.004**	−0.017
	(0.050)	(0.462)	(0.002)	(0.053)
Slope, altitude, rainfall, temperature and wind speed	0.096*	1.036**	0.003*	−0.049
	(0.048)	(0.486)	(0.001)	(0.060)
Observations: woredas	55	43	47	63

Notes: Each coefficient is from a separate regression. Robust standard errors are reported in parentheses. The difference in the number of observations is due to missing data for certain *woredas* and practices in the 2001 Agricultural Census.

border between the two regions. The effects remain quantitatively similar and significant across the different specifications.

In the alternative approach, as a first step we estimate a logistic regression based on pre-treatment annual outcome levels and obtain propensity scores. We then re-estimate equation (1) considering only pixels in the common support. Results are reported in column (3) of Table 3. We also consider a weighted regression approach where weights are the number of occurrences of pixels in the control group after we impose a common support in the propensity score (Heckman et al., 1998). The results related to this latter approach are presented in column (4). In both cases, we observe very similar effects to those estimated using the full sample.

Our results are also robust to the inclusion of *woreda*-specific time trends, the use of an alternative outcome variable (the monthly mean NDVI in place of the monthly maximum NDVI), the exclusion of individual control variables, and of the westernmost areas of Tigray and Amhara (see Table A2 and Table A3 of the Appendix).

6.2. Climate change adaptation

The CSA approach emphasises the crucial importance of building resilience to the negative effects of climate change (Lipper et al., 2018). In a context such as that of Ethiopia, where there is unequivocal evidence of a warming of the climate, with mean annual temperatures having increased by 1.3 degrees Celsius between 1960 and 2006 (Mcsweeney et al., 2010a; Mcsweeney et al., 2010b) and projected to continue to increase significantly in future decades (Aragie, 2013; Cline, 2007; Deressa and Hassan, 2009; FDRE, 2007; Mcsweeney et al., 2010a), climate-related risks pose a significant threat to farm-households' livelihoods, to agricultural systems and to the nation's economy (Aragie, 2013; Cline, 2007; Deressa and Hassan, 2009; FDRE, 2015; Mideksa, 2010; World Bank, 2008; World Bank, 2010; You and Ringler, 2010).

Adapting to climate change is therefore paramount for rural populations and adopting CSA practices can contribute to this endeavour. Tenure insecurity is often a barrier to the adoption of agricultural practices with climate-smart potential (Abdulai et al., 2011; Asfaw et al., 2016; FAO, 2017; Kpadonou et al., 2017; Lipper et al., 2018). Removing such a barrier can act as an enabler for CSA adoption, thereby enhancing the resilience of agricultural systems and reducing farm-households vulnerability to the adverse effects of climate change.

The main manifestations of a changing climate which threaten directly agricultural production systems in Ethiopia, including in the specific areas studied in this article, are abnormal dry and abnormal wet spells, which often result in droughts and floods (FDRE, 2015; Mersha and van Laerhoven, 2018; World Bank, 2006; World Bank, 2010; World Bank, 2011).

During the timeframe of our study, the use of the methodology presented in Section 5 led us to identify nine years where abnormally dry or abnormally wet conditions occurred during the *kiremt* season.[37] As indicated in Section 5, the *kiremt* season (June to September) corresponds to the rainy season in our study area.[38] Farm-households rely on rainfall during these months for their agricultural production and rainfall anomalies occurring during *kiremt* can impact farm harvest, total agricultural output and consequently the livelihoods and food security of farm-household members. Such impacts are indeed expected to be lower for farm-households having adopted climate change adaptation strategies, including the adoption of CSA.

Table 4 illustrates the results from the estimation of equation (1) when restricting our dataset to the years when adverse climate and weather events occurred. The results in Table 4 show that the effect of the treatment is positive and strongly statistically significant across the specifications and the estimators employed. The treatment effect is similar in magnitude to the results in Table 1, while the lower average NDVI confirms that greenness is lower, in general, in the years of excess/deficit of rainfall. The results reported in Table 4 provide evidence of the positive effect of the treatment on NDVI in the Tigray region when in presence of abnormal dry or wet spells. These results suggest that the treatment, by enhancing tenure security and adoption of CSA practices, reduced farm-households' vulnerability to adverse climate and weather events. In other words, the LRCP appears to have contributed to progress on the second objective of CSA, that is supporting farm-households in adapting to climate change.

The results from Table 4 remained largely persistent after we carried out a series of robustness checks to assess the sensitivity of our findings to alternative specifications of our model. The effect of the treatment was positive and statistically significant when we refined the treated and control areas (computing counterfactuals based on propensity scores, as in Section 6.1.1; employing different distances from the Tigray-Amhara regional border; excluding the westernmost areas of the two regions),

[37] In particular, five years were identified where conditions could be categorised as "mild" or "moderate" drought, namely the years 1991, 1992, 1997, 2002 and 2004, and four years - the years 1993, 1996, 1998 and 2000 - where conditions corresponded to the "slightly", "moderately" or "very" wet class (Palmer, 1965). As discussed in Section 5, we employ the same threshold (in absolute value) to identify dry and wet anomalies. The fact that three wet classes and two dry classes appear in our results is due to the PDSI values over the areas of interest during the timeframe of this study. In other words, our data show the presence of specific wet years that can be categorised as more extreme compared to the dry years.

[38] See also Figure A of the Appendix, which displays the total monthly rainfall across Ethiopia averaged over our study period (1991–2004).

and when we employed a different outcome variable (i.e. the monthly mean of NDVI instead of the monthly maximum of NDVI) (see Table A6–A8 of the Appendix).

7. Mechanisms

The results reported above show that the Tigray LRCP had positive effects on NDVI, both when employing our full dataset and when using a sub-dataset of years where adverse climate and weather events occurred. We argued that these results are indicative of a positive effect of the programme on the three CSA objectives over the landscapes of Tigray.

In the above sections we also pointed out that, due to the nature of our dataset, we are constrained to rely primarily on theory and on the empirical evidence available from the literature to uncover the mechanisms underlying such effects. We hypothesised that the positive effects of the LRCP on the CSA objectives occurred via an increase in tenure security and a consequent increase in CSA adoption.[39] Whilst data limitations prevent us from undertaking a formal causal analysis of such underlying mechanisms, we explore, in this section, the association between NDVI and CSA adoption to gauge the consistency of our main results with the hypothesised mechanisms.

Our choice of CSA strategies is constrained by data availability. In particular, the only official and publicly available source of data at the sub-national level is the Ethiopian Agricultural Census of 2001 (FDRE, 2003).[40] The Census provides information at the *woreda* level on rural holders' adoption of specific agricultural strategies.[41] By combining such data with NDVI values from our dataset, we can investigate, at the *woreda* level, the relationship between NDVI and CSA adoption.

We begin by examining the correlation between NDVI and the proportion of rural holders who planted permanent crops.[42] Column (1) of Table 5 shows that a positive correlation exists between these two variables in Tigray and Amhara (a scatterplot is also provided in panel a of Appendix Figure F). The positive correlation persists when including both time-variant and time-invariant control variables (slope, elevation and weather variables). These results suggest that investment in permanent crop production may indeed be associated with a positive effect on the three CSA objectives.

Yet, we cannot exclude that the permanent crops (trees/shrubs) might have been planted by farmers to secure their farmland, rather than being planted as a result of increased tenure security. The literature on land tenure security and farm-level investments, and in particular tree planting, reveals that a reverse causality may exist between the two variables (Brasselle et al., 2002; Deininger and Jin, 2006; Place, 2009). In particular, due to tenure insecurity, farmers may be prone to plant trees/shrubs at the boundaries of rural holdings (Kassa et al., 2011; Lovo, 2016). Ali et al. (2011), however, find reassuring evidence on the direction of causality in the context of Ethiopia. By studying the effects of tenure security on investment in trees/shrubs, they find that tenure security increases investment in coffee and chat, two of the most widely grown permanent crops in Ethiopia.

As a robustness check, we examine two additional indicators related to permanent crop production, namely the proportion of rural holders' land area planted with permanent crops and the number of planted trees per land area. The use of these complementary indicators strengthens our analysis, as these indicators can also help account for the distribution of trees/shrubs within the holdings. In other words, a higher density of permanent crops (in terms of land area and number of trees) can be indicative of tree/shrub planting within the holding, rather than at its boundaries. The correlations between NDVI and these two additional indicators are shown in columns (2) and (3) of Table 5, respectively (see also Figure F of the Appendix panels b and c for scatterplots illustrating these correlations). These results confirm the presence of a positive and significant correlation between NDVI and investment in permanent crops.

We also explore data on contour ploughing, a CSA strategy that can improve water infiltration and help enhance soil moisture, whilst reducing runoff, soil loss and erosion. Contour ploughing is considered a traditional soil and water conservation practice in Ethiopia (Mushir and Kedru, 2012; Amsalu and de Graaff, 2006), with traditional systems such as *terwah* and *derdero* showing clear benefits in terms of reduced runoff and soil loss (Gebreegziabher et al., 2009; Nyssen et al., 2011). We find some evidence of a positive correlation between NDVI and the use of contour ridges (Column (4) of Table 5 and Figure F of the Appendix panel d), although the correlation disappears when we control for average rainfall.

In summary, while the information provided in this section is merely suggestive of an association between NDVI and CSA adoption, it is reassuring to observe such a correlation. The presence of a positive relationship between NDVI and CSA adoption is in fact consistent with the mechanisms hypothesised to underlie our main results.

8. Conclusions

In this study, we re-examined the land tenure reform undertaken at the end of the 1990 s in the Tigray region of Ethiopia. Albeit the effects of this reform have been studied extensively (see, e.g., Ayele and Elias, 2018 for a review), our research complements the existing literature by employing a different source of data, by amplifying the geographic and temporal extent of the analysis, and by exploring the effects of the reform on a distinct set of objectives. In particular, this study employed an original panel dataset constructed from remote sensing satellite data to analyse, at a regional scale, the causal effects of the LRCP implemented in Tigray on the Climate Smart Agriculture (CSA) objectives. By applying a difference-in-differences strategy, we found that while adaptation and mitigation objectives were not explicitly embedded in the LRCP, the programme, by strengthening tenure security, increased

[39] Evidence from the literature on the positive effects of the LRCP in Tigray on tenure security and on the adoption of agricultural practices with climate-smart potential is provided in the literature review section (Section 2 above); see also Section 3 for a detailed description of the underlying channels via which those effects are hypothesised to occur.

[40] Datasets made publicly available by researchers, such as the Ethiopian Rural Household Surveys (ERHS) 1989–2009, have also been explored. However, the ERHS only include two villages in the Tigray region (Geblen and Haresaw), both located in the North-East of the region, very close to the Tigray-Afar regional border and four villages in the Amhara region, three of which are located in the South of the region, and can therefore not be considered as representative of the study area.

[41] Whilst the Central Statistical Agency of Ethiopia conducts agricultural surveys on an annual basis, 2001 represents the only year, within our period of analysis, for which data are available at the *woreda* level (employing the higher zonal or regional administrative levels would not provide sufficient observations for a relevant analysis to be undertaken). For this reason, we are not able to investigate changes before and after the reform, yet we can still provide evidence of correlation between these types of investment and NDVI to support the mechanism discussed above.

[42] According to the Agricultural Census, 27% of rural holders in Tigray and Amhara planted permanent crops (FDRE, 2003). Close to all of these permanent crop producers (98% of them) had also planted temporary crops on their holdings and were thus operating an agroforestry type of system, which is indeed a prime example of climate-smart integrated production system (FAO, 2017: module B5; ICRAF, 2019).

land related investments, which enhanced productivity as well as climate change adaptation and mitigation.[43]

These findings have relevant implications for both research and policy. They confirm and extend earlier findings from household-level surveys on the positive effects of the LRCP, specifying that such effects appear to have occurred at a regional scale on measures of productivity, climate change adaptation and climate change mitigation. As such, they provide a first empirical validation of the linkages between tenure reforms and the CSA objectives, thereby suggesting that land tenure reform programmes can play an important role in generating an enabling environment for CSA and in supporting the achievement of rural development objectives, including objectives associated with climate change. This is particularly encouraging for policymakers given that CSA objectives were not embedded in the original goals of land reformers in Ethiopia. In other words, further scope for enhancing sustainable increases in agricultural productivity, climate change adaptation and climate change mitigation by means of a land tenure reform exists. Land reformers can, for instance, ensure that participatory spaces are adequately set-up during the design of a tenure reform to engage with farmers (among other stakeholders) and subsequently prioritise interventions that are the most demanded and likely to incentivise farmers to adopt CSA strategies.

This research also confirms the importance of remote sensing satellite-based data for research and policy. Earth Observation (EO) data can prove a valuable source of data to analyse the effects of a policy on areas of interest. Such data can be particularly useful when other data sources, such as household-level surveys or census are scarce, do not comprise sets of relevant variables for the research questions at hand and/or may be prone to measurement error. The increased range of EO data consistently available at a high temporal and spatial resolution, developments in computing power and machine learning, as well as advances in modelled “ready-to-use” data products, offer growing opportunities for the use of such data in social science research and policy.

Indeed, this study is not immune to limitations. First, the NDVI can only be considered as a proxy for agricultural productivity and climate change mitigation. Although the evidence provided in this paper, combined with previous findings from the literature, supports the validity of NDVI as a measure of agricultural productivity and carbon uptake, more refined indicators of agricultural productivity and of greenhouse gas emissions/carbon sequestration could be investigated to corroborate or refute the results from this study. Second, additional quantitative and/or qualitative localised data sourced, for instance, from regionally representative household-level surveys and/or focus group discussions could be combined with remote sensing data to provide a deeper understanding on the various contextual factors surrounding the effects of the land tenure reform programme. In particular, these could help examine the underlying channels leading to the effects of the reform on the CSA objectives (i.e. increased tenure security and CSA adoption). In this study, data limitations prevented us from carrying out a formal causal analysis of these underlying mechanisms.[44] Finally, the research could be spatially and temporally extended to investigate the effects of the reform beyond the Tigray region and beyond 2004. This would require more precise information compared to what we were able to obtain on the specific dates and specific location of the implementation of the reform across the other regions of Ethiopia. We hope that the above elements can translate into valuable inputs for the realisation of further research.

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CRediT authorship contribution statement

Alexis Rampa: Conceptualization, Methodology, Writing – review & editing, Formal analysis, Writing – original draft, Visualization, Project administration. **Stefania Lovo:** Conceptualization, Methodology, Writing – review & editing, Formal analysis, Writing – original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

[43] Albeit the CSA approach emerged only in 2009 (FAO, 2009), that is a decade after the implementation of the LRCP in Tigray, it is an approach that features both modern and traditional agricultural practices and technologies. Indeed, practices that have traditionally been adopted by farm-households in Ethiopia, such as agroforestry, manure management, traditional conservation agriculture, micro-scale irrigation are all practices that have the potential to be considered “climate-smart” (FAO, 2016).

[44] Due to the nature of our dataset, we were constrained to rely primarily on the conceptual framework and on the available empirical literature to uncover these mechanisms. Nonetheless, we also found reassuring evidence of a correlation between NDVI and CSA adoption (Section 7), suggesting that our main results are indeed consistent with the outlined theory and with the empirical literature examining the effects of the LRCP in Tigray on tenure security and adoption of agricultural practices with climate-smart potential.

Table A1
Summary statistics.

		Pre-treatment period (1991–1998)						Post-treatment period (1999–2004)						All dates (1991–2004)					
		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
NDVI	January	0.35	0.08	0.37	0.08	0.34	0.07	0.37	0.08	0.38	0.08	0.36	0.08	0.36	0.08	0.37	0.09	0.35	0.08
	February	0.31	0.07	0.32	0.07	0.31	0.07	0.33	0.08	0.34	0.08	0.32	0.07	0.32	0.07	0.33	0.08	0.31	0.07
	March	0.30	0.08	0.31	0.08	0.29	0.08	0.30	0.07	0.31	0.07	0.29	0.07	0.30	0.08	0.31	0.08	0.29	0.07
	April	0.30	0.09	0.31	0.09	0.30	0.08	0.30	0.08	0.31	0.08	0.29	0.07	0.30	0.08	0.31	0.09	0.29	0.08
	May	0.36	0.09	0.37	0.09	0.34	0.09	0.34	0.08	0.35	0.09	0.33	0.07	0.35	0.09	0.36	0.09	0.34	0.08
	June	0.40	0.13	0.42	0.14	0.38	0.12	0.37	0.13	0.39	0.15	0.35	0.11	0.38	0.13	0.40	0.15	0.37	0.11
	July	0.48	0.15	0.51	0.16	0.45	0.14	0.50	0.16	0.52	0.16	0.47	0.14	0.49	0.16	0.51	0.16	0.46	0.14
	August	0.59	0.13	0.61	0.13	0.56	0.13	0.60	0.12	0.62	0.12	0.58	0.12	0.59	0.13	0.61	0.13	0.57	0.12
	September	0.62	0.13	0.64	0.13	0.61	0.13	0.64	0.12	0.65	0.11	0.63	0.11	0.63	0.12	0.65	0.12	0.62	0.12
	October	0.56	0.14	0.58	0.14	0.54	0.13	0.58	0.14	0.59	0.15	0.57	0.13	0.57	0.14	0.59	0.14	0.56	0.13
	November	0.47	0.11	0.49	0.12	0.45	0.10	0.50	0.12	0.52	0.13	0.48	0.11	0.48	0.12	0.51	0.12	0.46	0.11
	December	0.41	0.10	0.43	0.10	0.40	0.09	0.41	0.10	0.42	0.10	0.39	0.09	0.41	0.10	0.43	0.10	0.40	0.09
	Annual avg.	**0.43**	**0.16**	**0.45**	**0.16**	**0.41**	**0.15**	**0.44**	**0.16**	**0.45**	**0.17**	**0.42**	**0.15**	**0.43**	**0.16**	**0.45**	**0.16**	**0.42**	**0.15**
observations		**96,768**		**48,384**		**48,384**		**72,576**		**36,288**		**36,288**		**169,344**		**84,672**		**84,672**	
		Pre-treatment period (1991–1998)						**Post-treatment period (1999–2004)**						**All dates (1991–2004)**					
		All pixels		**Amhara_area**		**Tigray_area**		**All pixels**		**Amhara_area**		**Tigray_area**		**All pixels**		**Amhara_area**		**Tigray_area**	
		mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Precipitation (mm)	January	7.50	9.53	9.67	11.61	5.33	6.11	7.00	8.06	8.73	9.75	5.26	5.36	7.28	8.93	9.27	10.86	5.30	5.80
	February	8.25	10.13	11.26	11.99	5.23	6.56	6.34	7.22	8.54	8.22	4.15	5.19	7.43	9.04	10.09	10.63	4.77	6.04
	March	27.71	28.15	32.81	31.75	22.60	22.91	20.09	24.10	24.61	28.07	15.56	18.25	24.44	26.76	29.29	30.50	19.59	21.32
	April	42.47	34.94	48.20	37.39	36.75	31.29	32.70	26.28	38.00	27.74	27.40	23.58	38.28	31.89	43.83	33.97	32.74	28.62
	May	76.26	38.36	83.91	41.75	68.60	32.91	35.42	25.09	42.37	30.02	28.47	16.18	58.76	38.98	66.11	42.48	51.40	33.55
	June	111.18	75.69	114.74	76.47	107.63	74.74	105.73	69.11	111.58	72.69	99.87	64.81	108.84	72.99	113.38	74.89	104.30	70.75
	July	240.31	66.73	257.22	67.01	223.39	62.00	267.43	73.76	287.93	67.90	246.94	73.70	251.93	71.10	270.38	69.08	233.48	68.26
	August	263.90	76.01	275.32	66.08	252.48	83.24	291.99	67.38	303.97	52.93	280.01	77.42	275.94	73.76	287.60	62.42	264.28	81.93
	September	98.84	67.46	103.88	65.41	93.80	69.10	102.40	74.26	110.71	72.48	94.09	75.10	100.36	70.48	106.80	68.61	93.93	71.72
	October	40.04	38.02	49.64	43.45	30.44	28.64	40.93	40.33	51.76	47.40	30.10	27.79	40.42	39.03	50.55	45.19	30.29	28.28
	November	14.77	12.61	17.04	14.24	12.50	10.25	9.67	6.91	11.51	8.04	7.83	4.90	12.58	10.85	14.67	12.29	10.50	8.70
	December	6.05	7.24	7.41	8.49	4.70	5.40	5.93	6.67	7.64	7.82	4.22	4.68	6.00	7.00	7.51	8.21	4.49	5.11
	Annual avg.	**78.11**	**96.84**	**84.26**	**99.90**	**71.95**	**93.27**	**77.13**	**106.33**	**83.94**	**110.02**	**70.33**	**102.06**	**77.69**	**101.01**	**84.12**	**104.36**	**71.26**	**97.13**
observations		**96,768**		**48,384**		**48,384**		**72,576**		**36,288**		**36,288**		**169,344**		**84,672**		**84,672**	
		Pre-treatment period (1991–1998)						**Post-treatment period (1999–2004)**						**All dates (1991–2004)**					
		All pixels		**Amhara_area**		**Tigray_area**		**All pixels**		**Amhara_area**		**Tigray_area**		**All pixels**		**Amhara_area**		**Tigray_area**	
		mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Temperature (°C)	January	19.74	4.80	19.46	5.02	20.03	4.54	19.99	4.83	19.71	5.05	20.27	4.59	19.85	4.81	19.56	5.03	20.13	4.56
	February	20.64	4.70	20.35	4.92	20.93	4.44	21.67	5.11	21.31	5.31	22.03	4.88	21.08	4.91	20.76	5.11	21.40	4.66
	March	22.23	4.98	21.76	5.23	22.71	4.66	22.66	5.16	22.17	5.40	23.15	4.86	22.42	5.06	21.93	5.31	22.90	4.75
	April	23.37	5.31	22.60	5.55	24.15	4.95	23.70	5.34	22.94	5.60	24.46	4.95	23.51	5.33	22.75	5.58	24.28	4.95
	May	23.11	4.71	22.22	4.98	24.00	4.25	24.74	4.68	23.88	4.98	25.60	4.19	23.81	4.77	22.93	5.05	24.68	4.30
	June	22.17	3.87	21.35	4.34	23.00	3.13	22.80	4.07	21.85	4.51	23.74	3.31	22.44	3.97	21.56	4.42	23.32	3.23
	July	19.39	3.53	18.72	4.05	20.06	2.77	20.13	3.91	19.31	4.36	20.94	3.21	19.70	3.72	18.97	4.20	20.44	3.00
	August	19.15	3.45	18.51	3.98	19.78	2.68	19.68	3.60	18.96	4.12	20.41	2.82	19.38	3.52	18.71	4.04	20.05	2.76

(*continued on next page*)

Table A1 (*continued*)

		Pre-treatment period (1991–1998)						Post-treatment period (1999–2004)						All dates (1991–2004)					
		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
	September	20.25	3.80	19.44	4.23	21.06	3.12	21.12	3.98	20.18	4.37	22.06	3.28	20.62	3.90	19.76	4.30	21.49	3.23
	October	19.90	4.61	19.12	4.89	20.68	4.17	21.20	4.86	20.31	5.07	22.09	4.46	20.46	4.76	19.63	5.00	21.29	4.35
	November	19.65	5.01	19.09	5.27	20.20	4.68	20.67	5.33	20.02	5.57	21.32	4.98	20.09	5.17	19.49	5.42	20.68	4.84
	December	19.52	5.03	19.13	5.25	19.90	4.76	20.00	5.02	19.60	5.26	20.41	4.74	19.73	5.03	19.33	5.26	20.12	4.76
	Annual avg.	**20.76**	**4.76**	**20.15**	**5.03**	**21.38**	**4.38**	**21.53**	**4.94**	**20.85**	**5.21**	**22.21**	**4.56**	**21.09**	**4.85**	**20.45**	**5.12**	**21.73**	**4.48**
observations		**96,768**		**48,384**		**48,384**		**72,576**		**36,288**		**36,288**		**169,344**		**84,672**		**84,672**	

		Pre-treatment period (1991–1998)						Post-treatment period (1999–2004)						All dates (1991–2004)					
		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area		All pixels		Amhara_area		Tigray_area	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Wind speed (m/s)	January	1.60	0.35	1.58	0.39	1.62	0.31	1.62	0.30	1.60	0.34	1.63	0.26	1.61	0.33	1.59	0.37	1.62	0.29
	February	1.62	0.38	1.62	0.40	1.62	0.35	1.81	0.28	1.79	0.31	1.84	0.24	1.70	0.35	1.69	0.38	1.71	0.33
	March	1.72	0.39	1.68	0.41	1.75	0.37	1.86	0.37	1.79	0.39	1.93	0.33	1.78	0.39	1.73	0.41	1.83	0.36
	April	1.77	0.44	1.75	0.49	1.80	0.38	1.92	0.40	1.89	0.44	1.94	0.36	1.84	0.43	1.81	0.47	1.86	0.38
	May	1.91	0.40	1.87	0.45	1.95	0.35	2.05	0.36	2.00	0.40	2.10	0.31	1.97	0.39	1.93	0.43	2.01	0.34
	June	1.86	0.36	1.76	0.40	1.95	0.28	1.95	0.38	1.83	0.43	2.06	0.28	1.90	0.37	1.79	0.41	2.00	0.29
	July	1.71	0.44	1.63	0.50	1.79	0.34	1.76	0.46	1.70	0.53	1.82	0.37	1.73	0.45	1.66	0.52	1.80	0.35
	August	1.60	0.39	1.47	0.45	1.73	0.28	1.70	0.42	1.59	0.48	1.80	0.33	1.64	0.41	1.53	0.46	1.76	0.30
	September	1.60	0.35	1.52	0.40	1.67	0.27	1.55	0.33	1.52	0.40	1.59	0.24	1.58	0.35	1.52	0.40	1.64	0.26
	October	1.81	0.33	1.73	0.39	1.89	0.25	1.82	0.42	1.78	0.45	1.87	0.38	1.81	0.37	1.75	0.42	1.88	0.31
	November	1.51	0.36	1.47	0.38	1.55	0.33	1.67	0.27	1.68	0.29	1.67	0.23	1.58	0.33	1.56	0.36	1.60	0.30
	December	1.46	0.36	1.47	0.37	1.45	0.34	1.48	0.30	1.50	0.32	1.46	0.26	1.47	0.33	1.48	0.35	1.46	0.31
	Annual avg.	**1.68**	**0.40**	**1.63**	**0.44**	**1.73**	**0.36**	**1.77**	**0.40**	**1.72**	**0.43**	**1.81**	**0.35**	**1.72**	**0.40**	**1.67**	**0.44**	**1.76**	**0.36**
observations		**96,768**		**48,384**		**48,384**		**72,576**		**36,288**		**36,288**		**169,344**		**84,672**		**84,672**	

Notes: The table contains summary statistics (mean and standard deviation "sd") of the outcome variable (NDVI) and of the control variables (precipitation, temperature and wind speed) included in the preferred specification of the model presented in Section 5 (equation (1)). Both monthly and annual averages are provided, by treatment area (Amhara area, the never treated area, and Tigray, the treated area after 1998, as well as the combined area including all pixels in the Amhara area and in the Tigray area), and by treatment period (pre-treatment period and post-treatment period, as well as the combined period including the entire timeframe of the study).

Table A2
Effects of the LRCP on NDVI: further results of robustness checks.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:NDVI	Incl. Annual trend	Excl. temperature	Excl. rainfall	Excl. wind speed	Excl. westernmost areas
ATT	0.011***	0.008***	0.010**	0.008***	0.009***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
NDVI mean (st. dev.)	0.433 (0.137)	0.433 (0.137)	0.433 (0.137)	0.433 (0.137)	0.412 (0.118)
Observations (pixels)	169,344 (1,008)	169,344 (1,008)	169,344 (1,008)	169,344 (1,008)	125,160 (745)

Notes: Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5% level. FE: Fixed Effects. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables for columns (1) and (5); columns (2), (3) and (4) report results when omitting temperature, rainfall, and wind speed from the set of control variables, respectively. Column (5) reports results excluding pixels falling in the westernmost areas of each region (i.e. below 38-degree longitude for Tigray and below 37-degree longitude for Amhara).

Table A3
Effects of the LRCP on NDVI: results of robustness checks with alternative outcome variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: NDVI (mean)	Incl. Annual trend	75 km from border	50 km from border	Excl. temperature	Excl. rainfall	Excl. wind speed	Excl. westernmost areas
ATT	0.010***	0.008***	0.007***	0.007***	0.009**	0.007***	0.007***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI mean (st. dev.)	0.410 (0.129)	0.418 (0.132)	0.421 (0.133)	0.410 (0.129)	0.410 (0.129)	0.410 (0.129)	0.390 (0.111)
Observations (pixels)	169,344 (1,008)	131,208 (781)	88,536 (527)	169,344 (1,008)	169,344 (1,008)	169,344 (1,008)	125,160 (745)

Notes: Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5% level. FE: Fixed Effects. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables for columns (1) to (3) and column (7); columns (4), (5) and (6) report results when omitting temperature, rainfall, and wind speed from the set of control variables, respectively. Column (7) reports results excluding pixels falling in the westernmost areas of each region (i.e. below 38-degree longitude for Tigray and below 37-degree longitude for Amhara).

Table A4
Correlations between NDVI and agricultural productivity.

	Grains yields		Temporary crops yields	
	(1)	(2)	(3)	(4)
NDVI	1.892***	2.375***	1.899***	2.326***
	(0.426)	(0.460)	(0.424)	(0.478)
Region FE	No	Yes	No	Yes
Observations: *woredas*	63	63	63	63

Notes: Data on agricultural productivity (crop yields) are from the 2001 Ethiopian Agricultural Census (FDRE, 2003). Grains yields include cereal yields as well as yields of pulses and of oilseeds; Temporary crops include, beyond yields of grains, also yields of vegetables and of root crops. All measures of yields were log-transformed prior to estimation to facilitate interpretation. Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1% level. FE: Fixed Effects.

Table A5
Correlations between NDVI and Net Primary Productivity (NPP).

Datasets (years)	NPP_WaPOR (2009–2013)			NPP_MODIS (2001–2013)		
	(1)	(2)	(3)	(4)	(5)	(6)
NDVI	5.386***	5.382***	5.341***	4.606***	4.590***	4.516***
	(0.137)	(0.137)	(0.137)	(0.214)	(0.215)	(0.213)
Year FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	No	Yes	No	No	Yes
Pixel FE	No	No	No	No	No	No
Observations (*woredas*)	60,480 (71)	60,480 (71)	60,480 (71)	157,248 (71)	157,248 (71)	157,248 (71)

Notes: In columns (1) to (3) data on NPP are from the FAO Water Productivity Open Access Portal (WaPOR) (FAO, 2020), which are available from the year 2009. In columns (4) to (6) data on NPP are from the MODIS Terra dataset (Running et al., 2015), which are available from the year 2001. FE: Fixed Effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1% level.

Table A6
Effects of the LRCP on NDVI (climate change adaptation sub-dataset): results from two approaches to improve the counterfactual.

Climate change adaptation sub-dataset	(1)	(2)
Dependent variable: NDVI	In common support	Weighting
ATT	0.011***	0.010***
	(0.002)	(0.002)
Pixel FE	Yes	Yes
Month-Year FE	Yes	Yes
Controls	Yes	Yes
NDVI mean (st. dev.)	0.413 (0.128)	0.438 (0.134)
Observations (pixels)	83,268 (771)	78,840 (730)

Notes: Sub-dataset contains the years where adverse dry/wet conditions were identified, based on the PDSI data. Standard errors are block bootstrapped at the *woreda* level to account for correlated errors and the multi-step estimation procedure. *** indicates significance at 1%, ** at 5%, * at 10%. FE: Fixed Effects. Controls include the natural logarithm of temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as a full set of interactions between these variables.

Table A7
Effects of the LRCP on NDVI (climate change adaptation sub-dataset): further results of robustness checks.

Climate change adaptation sub-dataset	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: NDVI	Incl. Annual trend	75 km from border	50 km from border	Excl. temperature	Excl. rainfall	Excl. wind speed	Excl. westernmost areas
ATT	0.013***	0.009***	0.008**	0.009***	0.013**	0.010***	0.010***
	(0.004)	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI mean (st. dev.)	0.429 (0.133)	0.437 (0.136)	0.441 (0.136)	0.429 (0.133)	0.429 (0.133)	0.429 (0.133)	0.409 (0.114)
Observations (pixels)	108,864 (1,008)	84,348 (781)	56,916 (527)	108,864 (1,008)	108,864 (1,008)	108,864 (1,008)	80,460 (745)

Notes: Sub-dataset contains the years where adverse dry/wet conditions were identified, based on the PDSI data. Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5%, * at 10% level. FE: Fixed Effects. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables for columns (1) to (3) and column (7); columns (4), (5) and (6) report results when omitting temperature, rainfall, and wind speed from the set of control variables, respectively. Column (7) reports results excluding pixels falling in the westernmost areas of each region (i.e. below 38-degree longitude for Tigray and below 37-degree longitude for Amhara).

Table A8
Effects of the LRCP on NDVI (climate change adaptation sub-dataset): results of robustness checks with alternative outcome variable.

Climate change adaptation sub-dataset	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: NDVI (mean)	Incl. Annual trend	75 km from border	50 km from border	Excl. Temperature	Excl. Rainfall	Excl. wind speed	Excl. westernmost areas
ATT	0.012**	0.008***	0.007**	0.007***	0.011**	0.008***	0.007***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI mean (st. dev.)	0.405 (0.124)	0.413 (0.128)	0.417 (0.128)	0.405 (0.124)	0.405 (0.124)	0.405 (0.124)	0.386 (0.106)
Observations (pixels)	108,864 (1,008)	84,348 (781)	56,916 (527)	108,864 (1,008)	108,864 (1,008)	108,864 (1,008)	80,460 (745)

Notes: Sub-dataset contains the years where adverse dry/wet conditions were identified, based on the PDSI data. Standard errors (in parentheses) are clustered at the *woreda* level. *** Indicates significance at 1%, ** at 5%, * at 10% level. FE: Fixed Effects. Controls include temperature, temperature squared, precipitation, precipitation squared, and wind speed, as well as an interaction between these variables for columns (1) to (3) and column (7); columns (4), (5) and (6) report results when omitting temperature, rainfall, and wind speed from the set of control variables, respectively. Column (7) reports results excluding pixels falling in the westernmost areas of each region (i.e. below 38-degree longitude for Tigray and below 37-degree longitude for Amhara).

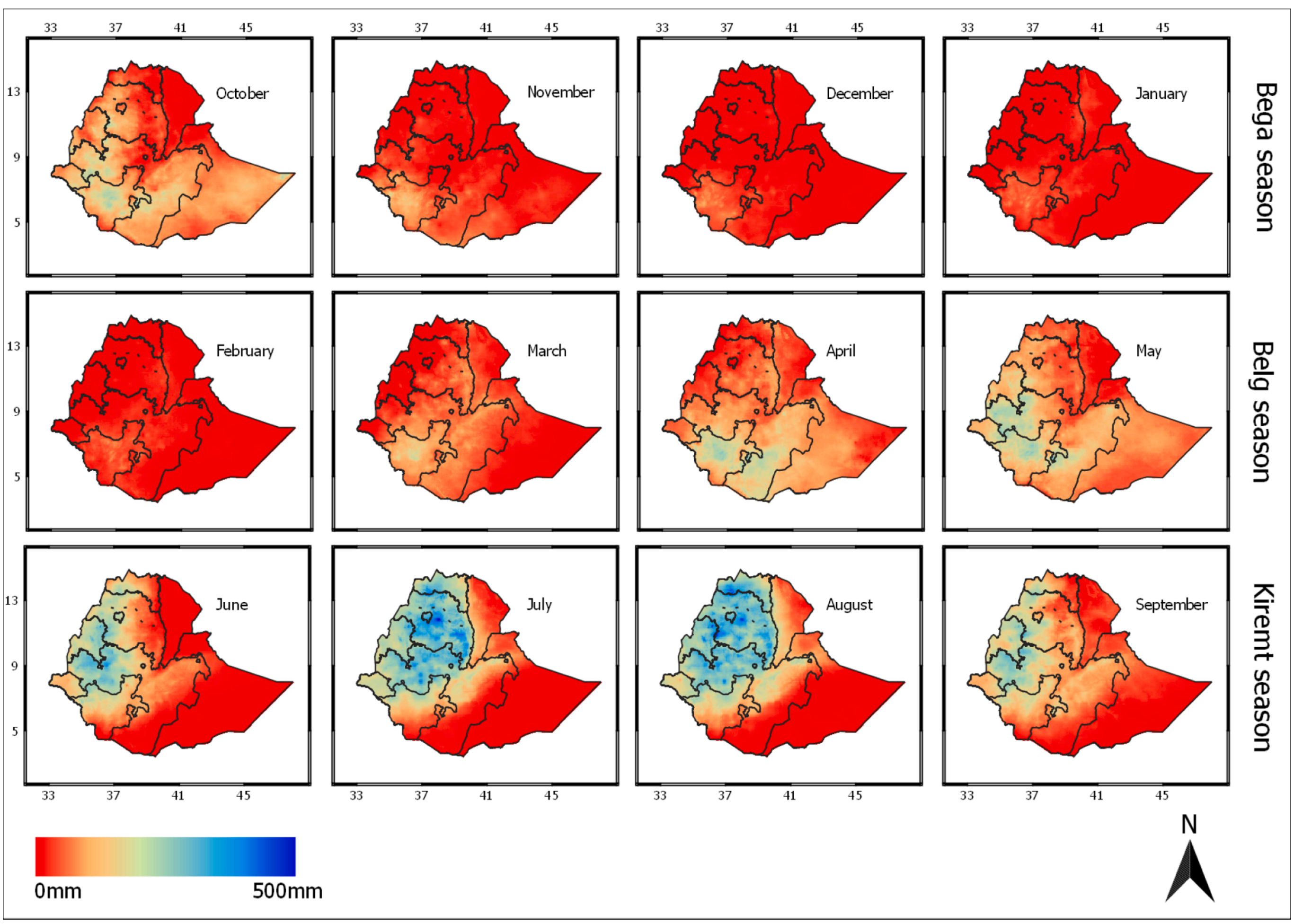

Figure A. Monthly rainfall (in mm) 1991–2004 average.
Source: Authors based on Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) data.

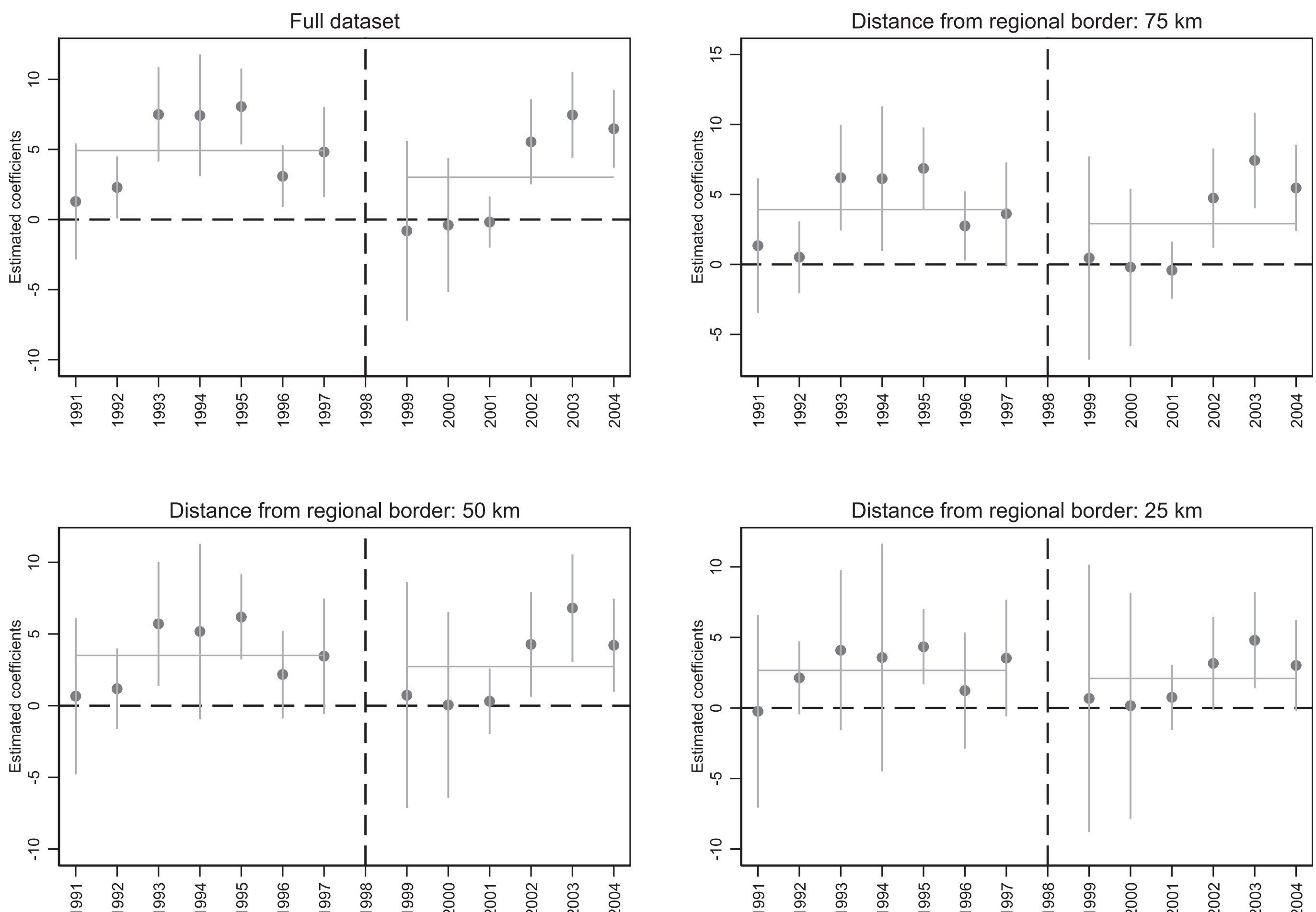

Figure B. Results from the event study with precipitation as dependent variable and different distances from the Tigray-Amhara regional border.
Notes: The coefficients are obtained from the estimation of event studies with precipitation as an outcome variable regressed on the treatment indicator (interacted with year dummy variables) and without controls. Standard errors are clustered at the *woreda* level, and the vertical bars represent 90 percent confidence intervals. Each panel corresponds to the results from the estimations based on different distances from the Tigray-Amhara regional border.

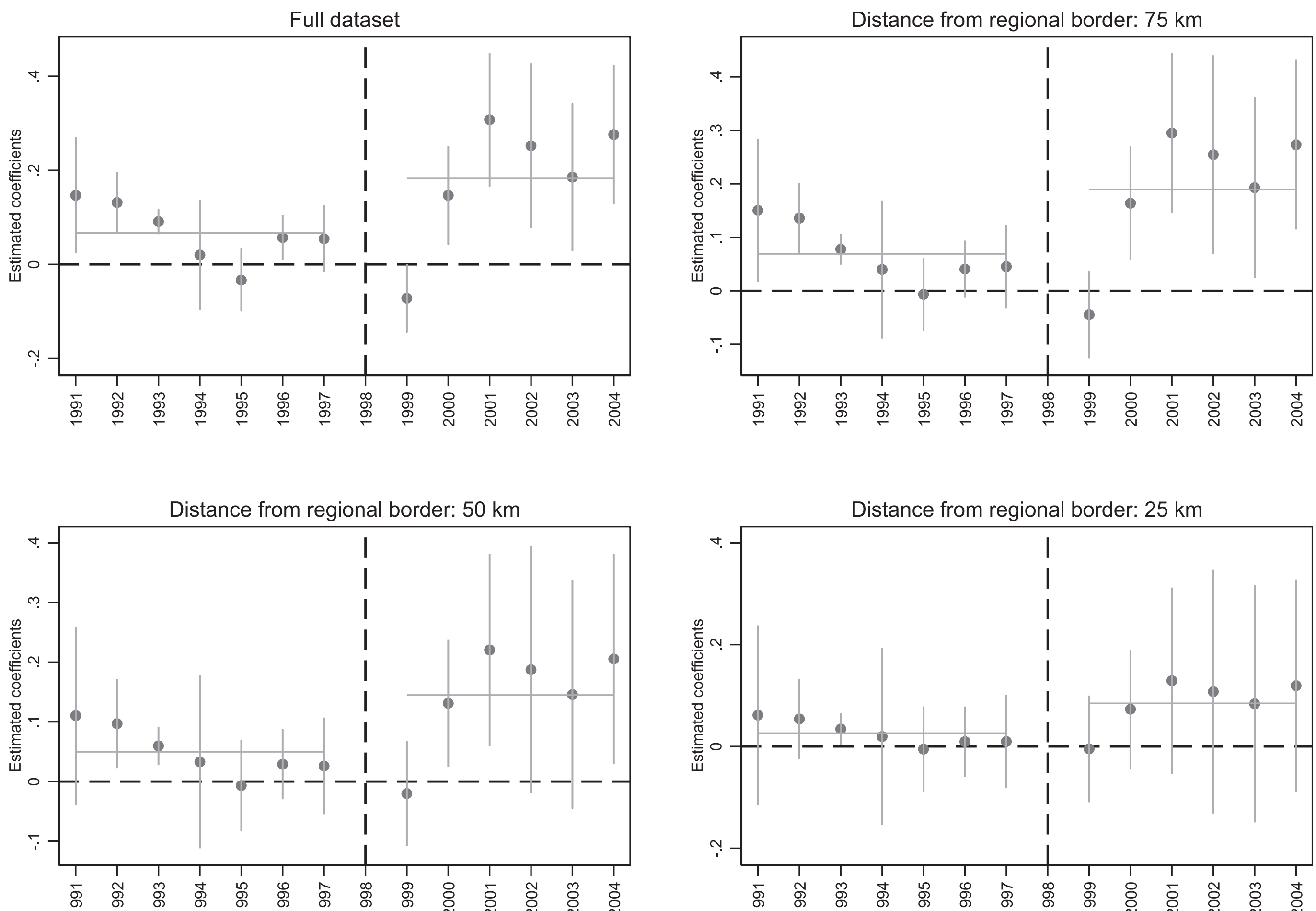

Figure C. Results from the event study with temperature as dependent variable and different distances from the Tigray-Amhara regional border.
Notes: The coefficients are obtained from the estimation of event studies with temperature as an outcome variable regressed on the treatment indicator (interacted with year dummy variables) and without controls. Standard errors are clustered at the *woreda* level, and the vertical bars represent 90 percent confidence intervals. Each panel corresponds to the results from the estimations based on different distances from the Tigray-Amhara regional border.

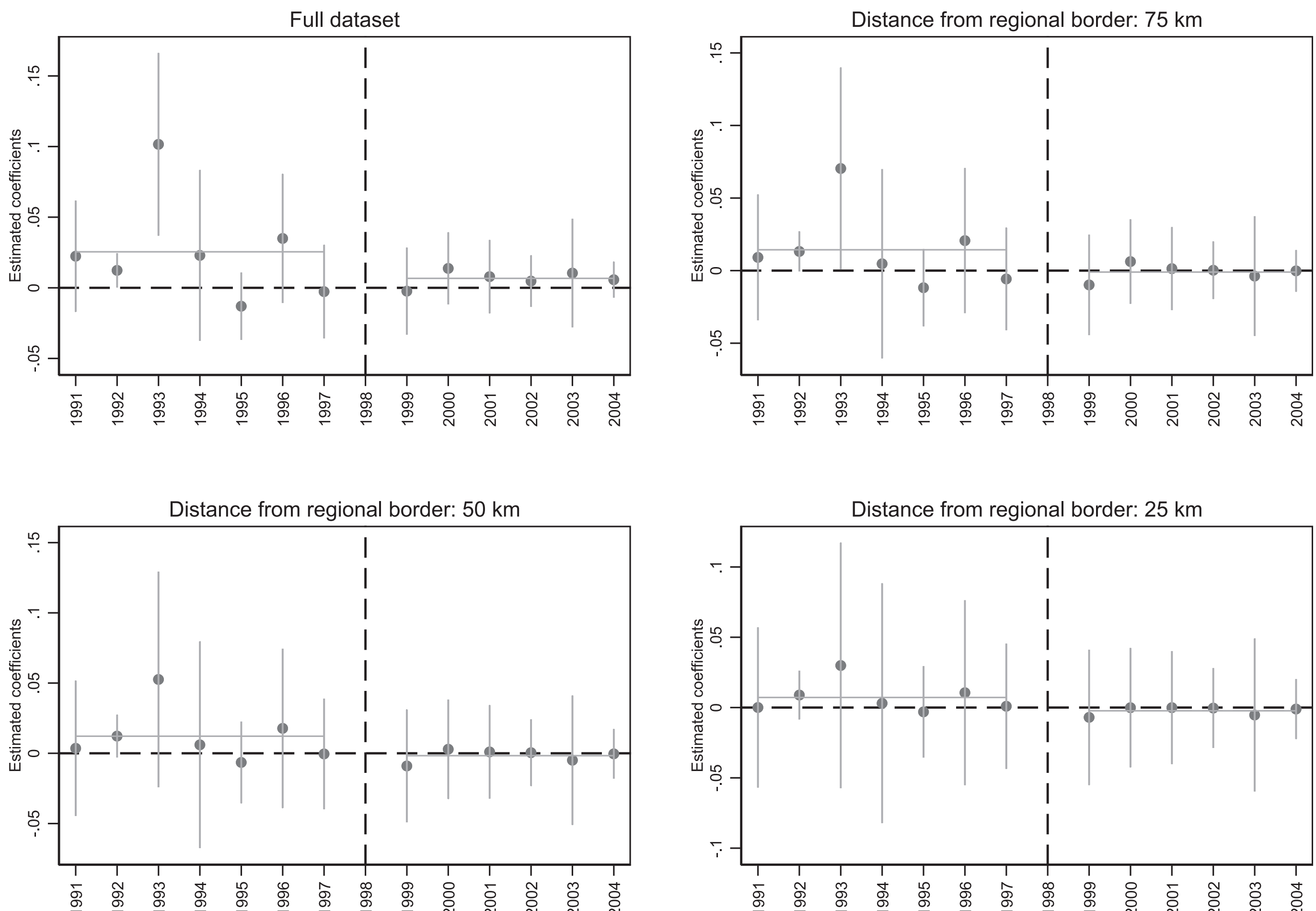

Figure D. Results from the event study with wind speed as dependent variable and different distances from the Tigray-Amhara regional border.
Notes: The coefficients are obtained from the estimation of event studies with wind speed as an outcome variable regressed on the treatment indicator (interacted with year dummy variables) and without controls. Standard errors are clustered at the *woreda* level, and the vertical bars represent 90 percent confidence intervals. Each panel corresponds to the results from the estimations based on different distances from the Tigray-Amhara regional border.

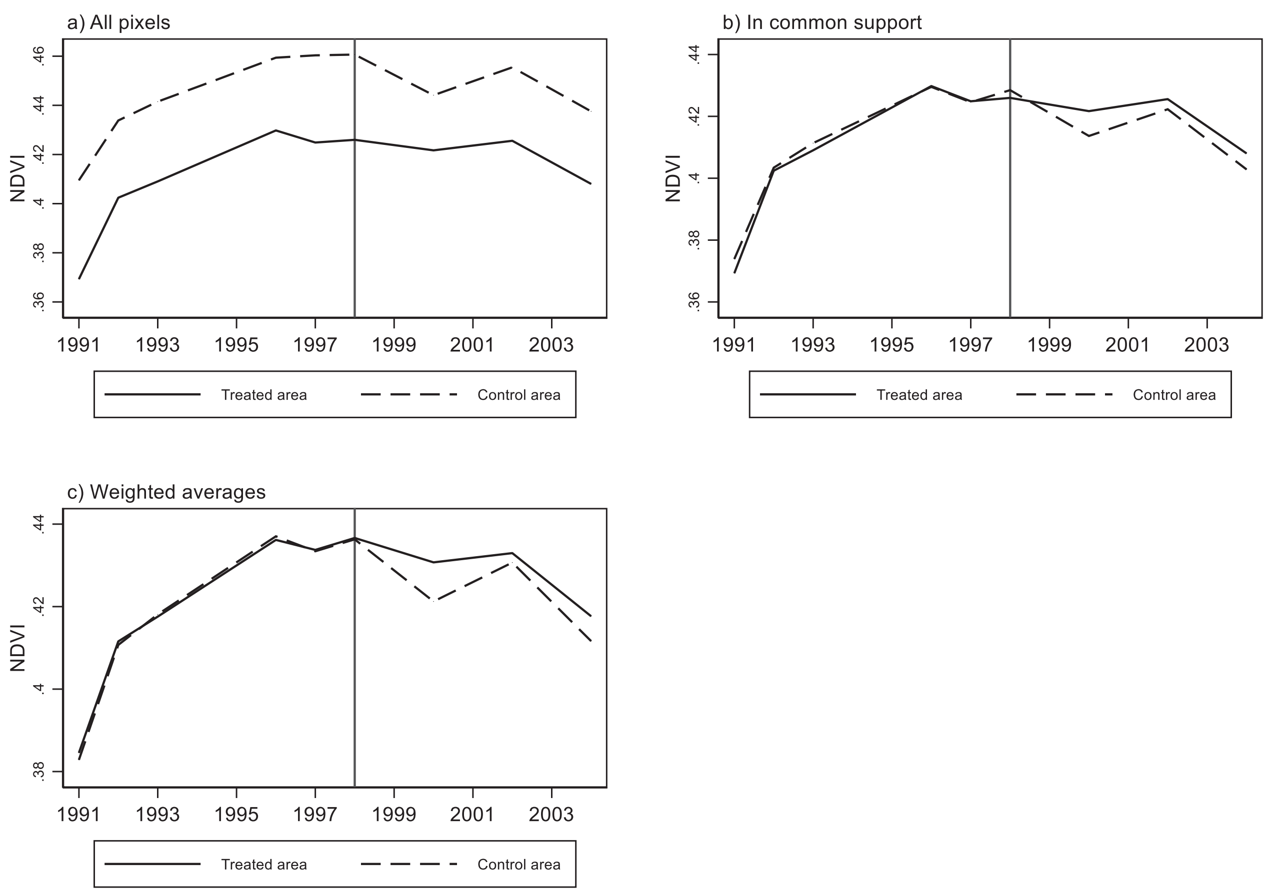

Figure E. NDVI values for treated and control areas (1991–2004) based on PDSI sub-dataset: different methods to define the counterfactual.
Notes: All panels are constructed from the sub-dataset containing the years where adverse dry/wet conditions were identified, based on the PDSI data. Panel a) displays the raw average NDVI values for all pixels included in the sub-dataset; panel b) shows NDVI averages only for pixels falling in the common support of a propensity score matching based on pre-reform levels of NDVI; panel c) shows weighted averages which use the occurrences of pixels in the control group, after matching on propensity scores with a bandwidth of 0.06.

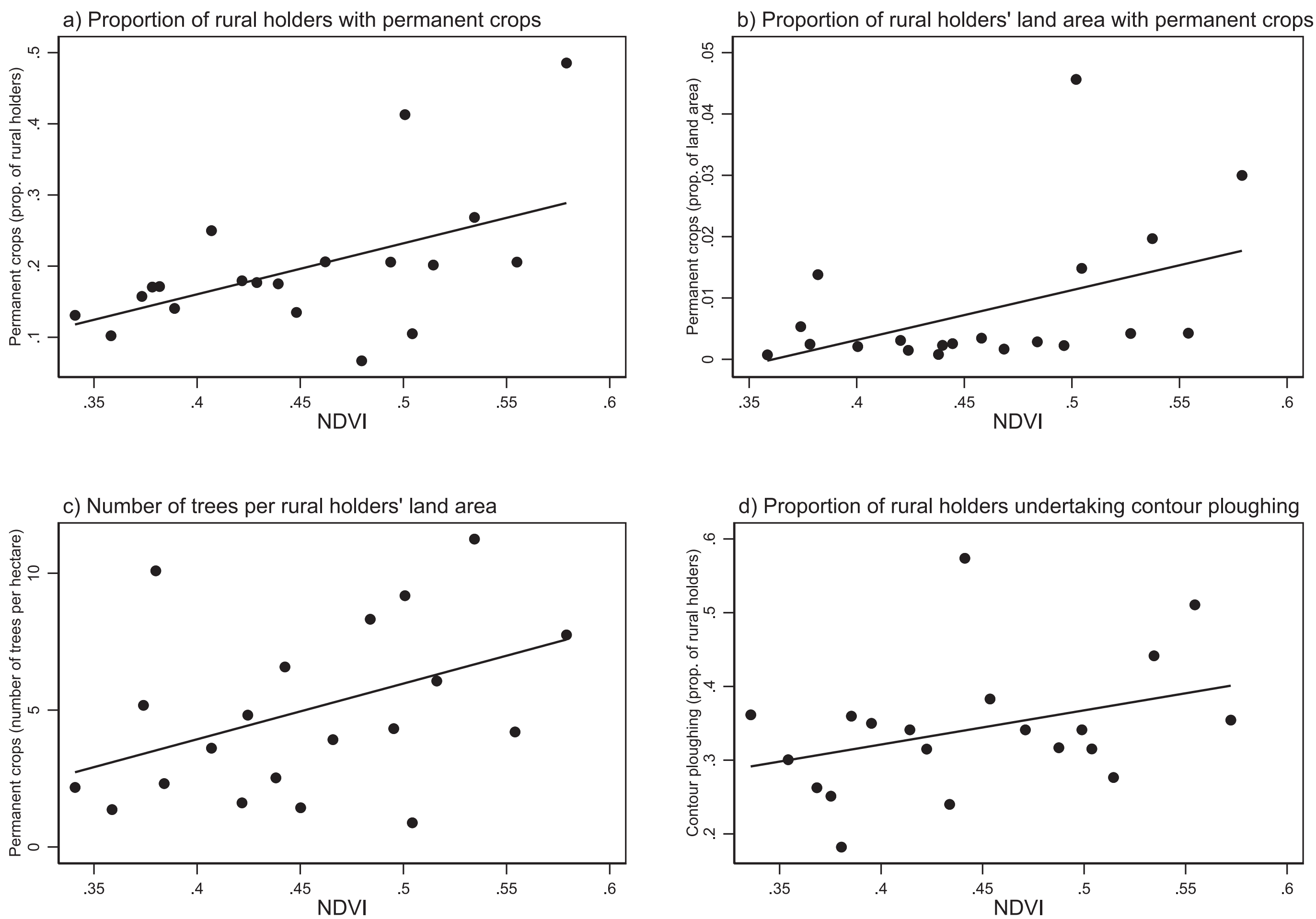

Figure F. Correlations between NDVI and CSA practices.
Notes: Graphs are obtained with data from FDRE (2003) and AVHRR NDVI 3 g (Pinzon and Tucker, 2014) by using 20 equal-size bins for the variable NDVI.

Appendix B. NDVI as a measure of productivity

In terms of agricultural productivity, early "ground-based *in situ*" studies using hand-held radiometers revealed the effectiveness of spectral data, and in particular of NDVI, in detecting plant vigour and in remotely measuring yields (Tucker et al., 1980). Since then, a large body of research has focused on the crop yield (or production) forecasting potential of NDVI, backed by the strong associations between NDVI and yields (or crop production) (Groten, 1993; Lewis et al., 1998; Mkhabela et al., 2005). A recent study undertaken in the Amhara region of Ethiopia found NDVI (as well as other vegetation indices) to be correlated with the yields of the main cultivated cereal crops, and particularly strong correlations were found between NDVI and teff and wheat yields, indicating that remote sensing data can have a promising role in predicting crop yields in these areas (Meshesha and Abeje, 2018). Furthermore, NDVI has recently been used as a measure of agricultural productivity in studies evaluating the economic impact of public programmes. Asher and Novosad (2020), for instance, estimated the impact of a large-scale rural road programme in India on five broad outcomes, including agricultural investment and yields. Utilising NDVI in their preferred measure of agricultural productivity, the authors found no significant effect of the programme on yields. Gazeaud and Stephane (2022) assessed the impact of the infrastructure component of the Government of Ethiopia's flagship productive safety net programme launched in 2005 on agricultural productivity. The authors first studied the relationship between values of NDVI and survey-based data on agricultural production and productivity in Ethiopia finding positive correlations, which justified the use of NDVI as their indicator of agricultural productivity. They then employed a difference-in-differences design and showed that the infrastructure component of the programme did not appear to have significant effects on agricultural productivity in the country.

In terms of climate change mitigation, the NDVI has been found in the literature to be strongly associated with different measures of carbon capture. Tucker et al. (1986) showed the presence of an inverse relationship between carbon dioxide (CO_2) concentrations in the atmosphere and NDVI, thereby demonstrating "the measurable link between atmospheric CO_2 drawdown and terrestrial NDVI dynamics" (Tucker et al., 1986:198). Furthermore, the NDVI, due to its strong correlation with the fraction of photosynthetically active solar radiation absorbed by plants, is commonly employed as a proxy of primary productivity (GEF, 2016; Sha et al., 2022; Sims et al., 2021; Vlek et al., 2010; Yengoh et al., 2015).[45] Gross Primary Productivity (GPP) represents the uptake of CO_2 by the standing biomass and Net Primary Productivity (NPP) results from the difference between GPP and autotrophic respiration (Ruimy et al., 1996; Sims et al., 2021). In other words, NPP represents the net amount of carbon assimilated after photosynthesis and autotrophic respiration over a specified time period (IPCC, 2021; UNCCD, 2017). NPP can thus be considered a direct indicator of carbon sequestration from vegetation (Sha et al., 2022). As Field et al. (1998) indicate, "NPP is a major determinant of carbon sinks [...] In terrestrial systems even modest increases in NPP potentially result in substantial carbon storage in plants and soils" (Field et al., 1998:237,239).

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[45] The basis of such an association is the different spectral signatures of the Earth's surface types. Vegetation has a different spectral signature compared to other surfaces such as bare ground, snow/ice, water, etc., in that plants, through photosynthesis, have strong absorption in the visible red band of the electromagnetic spectrum and high reflection in the near-infrared wavelength, which, as indicated in the main body of the text, are precisely the bands used in the computation of NDVI. Therefore, the NDVI represents a useful index of photosynthetic activity (Myneni et al., 1997; Purkis and Klemas, 2011).

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