

Using Satellite Imagery to Assess Impacts of Soil and Water Conservation Measures

Evidence from Ethiopia's Tana-Beles Watershed

Daniel Ayalew Ali

Klaus Deininger

Daniel Monchuk



WORLD BANK GROUP

Development Research Group

Agriculture and Rural Development Team

January 2018

Abstract

Although efforts at soil and water conservation are routinely viewed as instrumental in reducing vulnerability to climate change, their impact has rarely been quantified. Combining data on the timing and intensity of soil and water conservation interventions in select Ethiopian watersheds from 2009 to 2016 with a pixel-level panel of vegetative cover and soil moisture data derived from satellite imagery makes it possible to assess the biophysical impacts of such measures using a difference-in-differences specification. The results point

toward significant effects overall that vary by season, and that tree planting and other soil and water conservation activities are more effective on degraded than cultivated land. The results are consistent with before-after regressions for daily sediment load and stream flows in a subset of micro-watersheds. It thus appears that satellite imagery can improve the design and near-real-time monitoring of sustainable land management interventions for watersheds and landscape.

This paper is a product of the Agriculture and Rural Development Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The authors may be contacted at dali1@worldbank.org, kdeining@worldbank.org, and dmonchuk@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Using Satellite Imagery to Assess Impacts of Soil and Water Conservation Measures: Evidence from Ethiopia's Tana-Beles Watershed[¶]

Daniel Ayalew Ali

Klaus Deininger

Daniel Monchuk

The World Bank, Washington DC

dali1@worldbank.org, kdeininger@worldbank.org, dmonchuk@worldbank.org

[¶] We gratefully acknowledge funding support from the German Ministry for Economic Cooperation and Development through GIZ and the United Kingdom Department for International Development. We also thank the Amhara Bureau of Agriculture and the Tana Beles Integrated Water Resources Development team led by Mitiku Kebede for providing project data; Shewakena Abab, Anupam Anand, Nick Clinton, John Bryant Collier, Steve Danyo, Marguerite Duponchel, Ran Goldblatt, Nagaraja Rao Harshadeep, Thea Hilhorst, Paul Martin, Sisay Nune, and Rahel Wogayehu for support and insightful discussions; and participants in the 18th Annual World Bank Land and Poverty conference for helpful comments and Anne Grant for editing.

1. Introduction

Poor management of steep, erosion-prone, and often fragile tropical soils increases the exposure and vulnerability of poor people to climate change; by contributing to loss of vegetation and soil fertility, it may also heighten the severity of climate-induced shocks. Measures such as terracing, bunding, micro-dam construction, tree planting, and establishing agro-forestry systems have thus gained popularity and attracted major resources. In Africa alone, since 2006 the World Bank has invested more than US\$10 billion in sustainable land management (SLM) to reduce soil loss and increase soil moisture and vegetative cover. The goal is to help farmers adapt to the short-term effects of climate change and mitigate the impacts of climate-induced shocks over the medium term (World Bank 2017).

Yet while numerous studies have explored the biophysical variables that may be affected by SLM or soil and water conservation (SWC) activities and the associated microeconomic costs and benefits, there is as yet scant evidence on how much impact such investments have on watersheds or landscapes—the units at which these interventions are usually conducted. That makes it difficult to assess whether or how effectively these programs achieve their short- and longer-term objectives and to identify corrective actions in case they fail to do so.

One important issue is that SLM activities differ from the household-based interventions long analyzed by economists in three major ways, namely: (i) rather than improving livelihoods directly, a main goal is to better use vegetative cover to enhance the soil's capacity to capture and store water, reducing run-off and arresting soil erosion; (ii) the relevant unit of treatment is a watershed or a landscape with micro-watersheds, and their geographical scale is considerably larger, encompassing a number of communities and hundreds or even thousands of households depending on the basin under consideration and the water discharge point; and (iii) outcomes for any period are strongly affected by climatic variables and can be properly measured only if those variables are taken into account.

Recent advances in computing platforms and access to data have greatly improved the ability to evaluate these programs. Free access to archived medium-resolution imagery and processing power on cloud computing platforms such as Google Earth Engine (GEE) allows anyone to conduct analysis that a decade ago would have been costly and time-consuming even for experts. To demonstrate how such data can provide evidence that can serve as a basis for informed decision-making, we use Ethiopia's Tana Beles Integrated Water Resource Development Project (TBIWRD). Accessing and processing a large amount of readily available remotely sensed satellite images via GEE and combining them with information on the timing and location of interventions makes it possible to rigorously evaluate the impact of SWC activities on soil water content and photosynthetic activity at the pixel level.

From 2009 through 2015 the TBIWRD supported SWC and tree planting in 163 micro-watersheds covering some 860 km². The main objective was to improve vegetative cover in order to reduce water and sediment runoff so as to contribute to the long-term economic well-being of farmers and increase their resilience to future climate change and severe weather. Although lack of data on the exact location and timing of activities supported by the project imposes limitation in identifying effects of specific measures and the extent to which they vary with watershed features, we have aggregated annual micro-watershed data on areas of land, both cultivated and degraded, where SWC activities occurred and areas were planted with trees. Multispectral Landsat 7 imagery can then be used to create time series of vegetative conditions on the ground before and after the project by computing indices that are routinely used in the remote sensing literature. We use the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) to measure vegetation cover and photosynthetic activity and the Land Surface Water Index (LSWI) as a measure of plant and soil water content. To assess the impact of TBIWRD we compute seasonal averages for each index for 30x30 m pixels for the 5-year period before TBIWRD started and the 7 years of its activity. Defining a control area by drawing a 5-km buffer around treated areas allows us to use a difference-in-differences (DID) specification with pixel-level fixed effects for identification.

Our results support that project activities stimulated improvements in soil water content and vegetation cover. Estimated impacts are largest for changes in soil water-holding capacity (approximated by the LSWI) and estimated elasticities are highest for SWC on degraded land, followed by SWC on cultivated land and tree planting. For all indices considered here, the estimated impact of interventions completed two or more years ago is two to three times larger than the effect of those implemented during the last year, consistent with the notion that project benefits are sustained and accumulate over time. Estimated impacts vary by season and index in plausible ways: SWC activities are estimated to increase soil water content in rainy and dry seasons, which allows more vegetative cover to endure through the pre-rainy season, but planting trees results in an increase in vegetative cover that is spread equally across seasons.

Unfortunately, there are few comparable studies that could be used to interpret the size of the estimated coefficient to assess if, beyond statistical significance, estimated impacts are meaningful economically. To partly address this, we complement the study of indices based on satellite imagery with analysis of ground-based measurements of water flows and sediment loads directly related to TBIWRD project objectives. Data on daily volumes of water flow and the amount of sediment that were collected during the project at hydrological stations in a subset of treated micro-watersheds make it possible to independently cross-check the imagery-based results. While identification is weaker and the econometric approach less rigorous than for the imagery-based indices, we find a highly significant association between project-supported SWC activities and a meaningful reduction in sediment.

In what follows, section two discusses the far-reaching impacts of climate shocks and their link to resource degradation, the importance of these phenomena to Ethiopia, and the scope for analysis created by free access to archived medium-resolution imagery that now covers several decades. Section three describes the study area, the nature of the interventions, the data, and outcome variables of interest based on both remotely sensed imagery and ground-based measurements. Section four discusses the econometric approach and estimated impacts on indices derived from satellite imagery and ground measurements, and section five considers the policy implications of the findings.

2. Conceptual Framework

The increased frequency and severity of climate-related shocks are often thought to imply a need to enhance the resilience of farmers in developing countries in order to facilitate sustainable development. Yet unless the effectiveness of such interventions can be assessed, choosing an optimal level or mix of instruments may be difficult. Our analysis demonstrates how remote sensing can help address this issue; it looks at the advantages and disadvantages of commonly used indices in terms of the particular aspects of initiating sustainable land management interventions in Ethiopia.

2.1 The Far-Reaching Impacts of Climate Change

Global models nearly unanimously predicted that climate change would result in more frequent and severe weather shocks and ultimately to consequences from longer-term shifts in temperature, rainfall patterns, and water availability. History suggests that rising temperatures substantially reduce growth rates, agricultural and industrial output, and political stability, so that their negative impacts on poor countries are likely to be substantial (Dell et al. 2012).

While these qualitative effects of climate change have been known for some time, recent studies have increasingly quantified the size and incidence of their consequences. Although trade with countries less negatively affected by, or even benefitting from, climate change can mitigate adverse effects (Lybbert et al. 2014), agricultural losses are still estimated to reach one-sixth of total crop value (Costinot et al. 2016). Beyond effects on output, climate shocks affect human capital accumulation (Dinkelman 2015) and contribute to intra- and inter-country migration. This may give rise to urbanization without growth (Gollin et al. 2013), where, partly as a result of the difficulty of providing services and enforcing planning standards, costs are high and agglomeration benefits are low (Venables 2017), a pattern already observed in some parts of Africa (Henderson et al. 2017).

Three factors make it difficult to discern the most effective and sustainable types of interventions. First, soil erosion and changes in water content, the main effects of certain interventions, are difficult to observe; traditional methods of information collection, such as household surveys, are ineffective. Both density of

vegetation and household welfare would at best pick up second-order effects. Second, as interventions are applied to watersheds, the effects will be dispersed over large areas, affected by significant inter-temporal fluctuations of climate or weather. Establishing causality by separating signal from noise will require high-frequency data. Finally, often no good baseline or pre-intervention data are available for intervention areas.

Although the most immediate impacts of a changing climate will be on natural vegetation, it also affects livelihoods and has implications on rates of short- or longer-term migration. In the last 50 years, as Sub-Saharan Africa has become considerably drier, climate shocks have accelerated rural-urban migration (Henderson et al. 2017). Greater demand for urban jobs can exert downward pressure on wages and trigger migration to more distant places or other countries, possibly with far-reaching effects (Maurel and Tuccio 2016). Beyond the impact on economic growth, climate-induced shocks have been linked to higher incidence of civil conflict in Brazil (Naidoo et al. 2009) and Somalia (Maystadt and Ecker 2014), and over long historical periods in the Arab Republic of Egypt (Chaney 2013) and China (Chen 2015; Kung and Bai 2011) where it has also been shown that agronomic advances can help to mitigate these effects (Jia 2014).

Climate change can affect human capital directly or indirectly. For example, the burden of consumption smoothing may be disproportionately borne by pregnant women, affecting fetal development and long-term human capital accumulation. Exposure to extreme weather in utero or during early childhood has indeed been shown to have had lasting effects on human capital and ability in South Africa (Dinkelman 2015), the Philippines (Villa and Bevis 2017), Nepal (Tiwari et al. 2017), and Mongolia (Grosso and Kraehnert 2016).

2.2 Soil and Water Conservation in Ethiopia

The total cost of economic losses from soil degradation due to changes in land use and land cover has been estimated at US\$231 billion, 0.41 percent of global GDP (Nkonya et al. 2016), adding to the urgency of taking action. Efforts to halt soil degradation are generally advocated as a promising strategy to not only increase farmer resilience to climate shocks in the short term, but also to deal with the underlying causes in the medium term.

There is evidence that in Ethiopia, soil degradation poses immediate challenges to farmer livelihoods and negatively affects the provision of local and global public goods, threatening to undermine longer-term economic performance.¹ To address such threats, sustainable land management features prominently in the country's development strategy.² Although large amounts have been spent on SWC programs, their impacts are not always evident. For example a recent evaluation of the Ethiopia Sustainable Land Management

¹ See Gebreselassie, Kirui, and Mirzabaev (2016) and Nkonya et al. (2016) for evidence on losses of both productivity and ecosystem services such as carbon sequestration, biodiversity, genetic information, and cultural services.

² The 2010–15 Growth and Transformation Plan prioritized investment in soil and water conservation and the 2009–23 Ethiopia Strategic Investment Framework for Sustainable Land Management is designed to scale up sustainable land management to enhance productivity.

Project (SLMP), an intervention very similar to the one discussed here, found that a farmer's participation in the project was not associated with significantly higher production (Schmidt and Tadesse 2017).

One reason for finding limited or insignificant impacts from SWC interventions may be that such structures mature slowly; and even if they increase profitability in the long term (Kassie et al. 2008), sustaining them until benefits are realized requires short-term sacrifices that may be unaffordable for small farmers faced with subsistence constraints and limited credit access.³ Adoption of SLM practices can be affected by many factors, among them tenure security (Melesse and Bulte 2015), the time profile of benefits (Adgo, Teshome and Mati 2013), credit market functioning (Tesfaye et al. 2016), partial appropriability of benefits (Shiferaw and Holden 1999), limited risk-bearing capacity or social capital (Wossen, Berger, and Di Falco et al. 2015), and coordination failures deeply rooted in local history and socioeconomic structure (Smit et al. 2017).

Ethiopian farmers are well-aware of soil fertility problems (Tefera and Sterk 2010) and accept contracts to control soil erosion if the benefits exceed the cost (Tesfaye and Brouwer 2012). This has led to a consensus that intervention packages that are adapted to local conditions and pair SWC activities with infrastructure investments and support for the necessary inputs or compensation for labor are most conducive to long-term success (Schmidt et al. 2017). While GIS-based terrain modeling, combined with field observations, can be used to identify hotspots for interventions (Tamene et al. 2017) and SWC measures are likely to have clear impact (Schmidt and Zemadim 2015), also needed are economic analysis and a link to the biophysical relationships of individual farms (Ekbohm 2008) or larger agro-ecological units (Kassie et al. 2008). In principle, real-time feedback based on remotely sensed imagery could help make it possible not only to assess the extent to which desired impacts are realized, but also to adjust interventions in an iterative evidence-driven process. Yet although there are numerous studies of deforestation as an outcome variable, there has been little use of such data at finer spatial and temporal resolution.

2.3 Remotely Sensed Imagery and SLM Impacts

Plants absorb light in the 0.6-0.7 μ m wavelengths and reflect strongly in near infrared. Sensors for land surface analysis collect data in bands approximating these wavelengths to generate indicators of vegetation density, plant phenology, and photosynthetic activity or soil water content. Indices for these parameters can be obtained by differencing or computing ratios of red and near infrared (NIR) bands, possibly drawing on additional bands to eliminate effects of atmospheric aerosols or soil background (blue reflectance) and short-wave infrared (SWIR) to estimate leaf water content (Reed, Schwartz, and Xiao 2009).

³ Alternative explanations might be benefit spillovers to non-project areas or measurement errors.

A widely used index is the NDVI, defined as the normalized ratio between NIR and red bands (Tucker 1979) and scaled to fall in the range of +1 to -1.⁴ The NDVI is closely correlated with the leaf area index, a biophysical measure of the vegetation canopy (Gao et al. 2000), and has also been used to estimate carbon stocks. Photosynthetically absorbed radiation (FAPAR) is a function of the NDVI (Myneni et al. 2002), prompting wide use of the index in global models of gross or net primary biomass production (Justice et al. 1998) and for more localized estimates of soil erosion (Tadesse et al. 2017). To overcome the NDVI's limitations, especially a tendency to asymptotically saturate that limits its usefulness for dense canopies or bare soils, a soil-adjusted vegetation index or SAVI (Huete 1988) and a modified (Qi et al. 1994) or generalized SAVI have been suggested (Gilabert et al. 2002).⁵

In addition to the measures of photosynthetic activity that can be derived from the measures mentioned, thermal infrared bands can help to monitor evapotranspiration (Semmens et al. 2016) and plant or soil water content. The LSWI, based on the normalized ratio between NIR and SWIR bands (Xiao et al. 2002) also ranges from 1 to -1, with positive values for green vegetation and negative ones for dried (brown) leaves. It usefully complements the NDVI (Sakamoto et al. 2007), especially as an indicator of droughts or floods (Bajgain et al. 2015). Comparing seasonal cycles of NDVI and LSWI for different types of vegetation (deciduous broadleaf or evergreen needle forest, temperate grassland, cropland, and tropical moist forest) suggests that, except for cropland, values of these indices differ considerably from each other, with the LSWI finding more pronounced intra-seasonal variation than the NDVI (Xiao et al. 2009).

Though the potential for using remotely sensed imagery to measure vegetative cover has been available for some time, recent advances in access to data and computing platforms have greatly enhanced the scope for using these in routine program evaluations. Since the late 1970s optical sensors on satellites in the Landsat family have been providing data at reasonably high levels of temporal and spatial resolution (Markham and Helder 2012; Schott et al. 2012), a fact exploited for monitoring changes in global forest cover over rather long periods (Hansen et al. 2013), and in ways that can be updated in near-real time given the satellite's 16-day revisit time. Free public access to the entire Landsat archive (Wulder et al. 2012) and the availability of powerful free computing platforms greatly reduce the related costs. With GEE allowing access to vast amounts of consistently preprocessed imagery in the cloud, it is possible to generate time series of land cover classifications at pixel level (Gómez, White, and Wulder 2016) without time- and hardware-intensive processing. Resulting data can be used for a range of policy purposes, such as analysis of changes in forest

⁴ Areas with values close to -1 are water bodies; those around zero (-0.1 to 0.1) correspond to barren areas of road, sand, or snow; values 0.2 to 0.5 represent crops, shrubs, and grassland; and values above 0.5 correspond to dense vegetation.

⁵ A related measure is the EVI, which is calculated from red, NIR, and blue bands (Huete et al. 1997), is linearly correlated to the green leaf area index in crop fields (Boegh et al. 2002), is very sensitive to variation in canopy conditions (Huete et al. 2002), and is less affected by atmospheric aerosol contamination (Xiao et al. 2003).

cover (Hansen et al. 2016) to manage protected areas, or as measures of evapotranspiration to help manage water resources (Anderson et al. 2012).

3. Data, Descriptive Statistics, and Analytical Approach

Treatment variables, annual information on which is provided by the project monitoring system, are the share of a micro-watershed covered by SWC measures on cultivated or degraded land and new tree planting, respectively. We define a 5-km buffer around treated watersheds to serve as a comparison and source of control pixels and use a DID approach with pixel-level fixed effects to assess how the cumulative area treated affects mean photosynthetic activity, vegetation cover, and plant or soil water content in different seasons. Outcome data are aggregated from different indices based on biweekly Landsat 7 imagery for roughly 2.8 million pixels at 30m resolution. For the five micro-watersheds where daily information on water flow and sediment load was collected, this is complemented with a before-after assessment of how treatment affected these variables.

3.1 Nature of Intervention and Study Area

From 2009 through 2015, TBWIRD supported watershed planning and institutional strengthening in the entire Tana-Beles sub-basin and specific SLM activities in five critical watersheds covering some 860 km² (see map, figure 1). Table 1 illustrates that, at mean elevations of 2,300 to 3,000 m with average slopes of about 10 degrees, project watersheds seem susceptible to soil erosion. Each critical watershed comprises 25 to 40 micro-watersheds, defined as geographical units with a single point of water discharge. Micro-watershed boundaries and the drainage from each based on a 30m x 30m resolution ASTER digital elevation model (DEM) are illustrated in figure 2.⁶ The figure also illustrates the location of five hydrological stations. At each of these, daily measurements of water flow and turbidity were taken by community members who had been trained in the use of simple techniques and were regularly supervised by expatriate staff—part of an initiative to build local capacity for better understanding factors leading to soil erosion and downstream impacts of SWC measures. Although only collected after 2009, these readings provide outcome measures that can help cross-check results based solely on remotely sensed data.

We analyze the impact of three types of TBIWRD-supported interventions: (i) establishment of SWC structures, such as terraces, bunds, and physical vetiver grass barriers to limit runoff on land already cultivated; (ii) construction of micro-basins, terracing, bunding, area closures, and other conservation structures on non-cultivated land, such as hillsides and land used for grazing and forestry; and (iii) new tree plantings to establish agroforestry systems to stabilize landscape and produce timber and fuelwood. Panel

⁶ In addition to imagery, we generate elevation for each pixel using the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) data (Farr et al. 2007) with a 1 arc-second (30m) resolution.

2 of table 1 illustrates that by the end of the project in 2015, some 63 percent of cultivated land and 22 percent of degraded land had been covered by SWC measures and 8 percent of the project area with tree plantings. The cumulative area ultimately affected by the measures (see appendix table 1) suggests that, after a slow start in 2009, when there was activity on only about 3 percent of the project area (2.5% of cultivated land, 0.4% of degraded land, and 0.1% of newly planted area), activity picked up, to achieve the totals shown in table 1.

Data on the precise location and timing of project interventions are unfortunately not available. Instead, for each type of intervention we have annual data on area affected at the micro-watershed level, which we use in the regressions as a proxy for treatment intensity, as detailed below.⁷ Using a DID strategy, variations over time in micro-watershed coverage, together with the geographic discontinuity created by micro-watershed boundaries, can provide a basis for identifying project impacts on vegetation cover and soil moisture. The impact of such activities can then be evaluated beyond the effects of the project's planning and institution-building components or other initiatives (possibly building on institutional capacity created by TBIWRD) to establish SWC structures. The estimated effects of SLM investment are thus likely to be conservative.⁸

Rainfall data used in this study are based on the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which integrate 0.05° (approximately 5 km) resolution satellite imagery with ground-based weather station data to create gridded rainfall time series with 5-day temporal resolution (Funk et al. 2014). Daily rainfall was also measured at the five hydro-stations mentioned earlier; figure 3 shows the rainfall patterns in these areas during the project period. The basis for aggregating rainfall for regression purposes is Ethiopia's three seasons (Ethiopia National Meteorology Agency 2017).⁹ As table 1, panel 3, illustrates, the study areas receive some 1,500 mm of rain annually: 77 percent in the rainy season, 15 percent in the pre-rainy season, and 8 percent in the dry season. Control and treatment areas are very similar in terms of mean elevation (2,464–2,522 m) and slope (11.28° and 11.76°), and, as shown in table 2, columns 7 and 8, seasonal rainfall patterns.

⁷ While specific interventions may be reported in different units (e.g., the length of terraces constructed is in km rather than ha) for reporting purposes, local development agents convert these into the area affected.

⁸ One way to correct for such bias could be to select control areas from outside the Tana-Beles sub-basins and use matching techniques, but there would be no way to account for differences in watershed demographic profiles, cultural characteristics, and landscapes.

⁹ Each season covers four months: October 1 to January 31 is the dry season (*Bega*), February 1 to May 31 the pre-rainy season (*Belg*), and June 1 to September 30 the rainy season (*Kiremt*).

3.2 Outcome Variables

Bands from Landsat 7 imagery, accessed and processed using the GEE developer platform (GEE 2017),¹⁰ are used to construct pixel-level averages of NDVI, SAVI, and LSWI for each year and season.¹¹ At a pixel size of 30m x 30m, the average micro-watershed is covered by 5,951 pixels, well above the 84 pixels that would be available if we used MODIS.¹² With Landsat's revisit frequency of 16 days, this yields a maximum of 7–8 observations per season, though the actual value may be lower owing to cloud cover and failure of the satellite's scan line corrector after May 31, 2003.¹³ Before computing these indices, band values are converted to top-of-atmosphere reflectance (Zhu and Woodcock 2012), and a masking routine (Zhu et al. 2015) is used to exclude pixels "contaminated" by clouds, shadows, water, etc.). We assume that missing values are randomly distributed and thus enter the error term rather than biasing our estimates.

We used archived imagery of consistent quality during the pre-intervention period to obtain information for the 12-year period starting in 2005 with the dry season (Oct. 2004-Jan. 2005) and ending in 2016 with the rainy season (June–Sep.). Control areas were defined by drawing a 5-km buffer around critical TBIWRD watersheds (see figure 4). With some 2.8 million pixels having valid data per season, the quantity was too large to process; even aggregating biweekly observations to seasonal averages for the three annual seasons in each of the 12 years covered would result in about 100 million observations.

Summary statistics of outcome variables for control and treatment areas in pre- and post-treatment years (table 2) illustrate three observations. First, for all indicators inter-season variability is high, with peak values in the rainy season, followed by the dry and the pre-rainy season. Variation is highest for the NDVI, followed by the LSWI -the only index with marginally negative values, which indicates wilting of leaves in the pre-rainy season- and the SAVI. Second values of the indices for the project area are marginally above those for control areas throughout. Finally, discerning different trends from the data in the table requires greater disaggregation.

Nonparametric kernel-weighted local polynomial regressions against time (figure 5) point to a positive trend in all outcome indicators for control and treatment areas. They also support the notion of parallel trends in the pre-intervention period and divergence between treatment and control areas thereafter in a way

¹⁰ GEE is a cloud-based platform used to access and process large collections of satellite imagery. Given the volume of raw imagery and computational power necessary, without GEE it would have been very difficult, if not impossible, to conduct this type of analysis. Once processed in GEE, the data and variables of interest are exported as individual raster files and a batch process is used to extract pixel-level data. to facilitate merging across data sets Each pixel is assigned a unique identifier based on longitude and latitude.

¹¹ Beforehand, band values are converted to top-of-atmosphere reflectance using a masking routine (Zhu and Woodcock 2014) to exclude "contaminated" pixels. such as clouds, shadows, and water cover, that can result in unreliable values. Also filtered out in the masking process are problematic bands appearing in LS7 imagery due to a malfunctioning scan line corrector in the LS7 satellite, which renders about 22 percent of the data unusable (Irons, Dwyer, and Barsi 2012).

¹² While the MODIS two-day revisit frequency provides higher temporal resolution, we think the spatial resolution more than compensates for this.

¹³ The masking process filters out the problematic bands in LS7 imagery discussed above in footnote 11 (Irons et al. 2012).

that is consistent with the notion of positive treatment effects. As graphs control neither for treatment intensity nor for other time-(in)variant factors, econometric analysis is needed.

The intensity of runoff and the amount of sediment dissolved as measures of soil erosion link directly to TWIWRD's project objective. Simple field methods (Herweg 1996) suggest annual soil losses between 24 and 160 tons/ha and year (Tefera and Sterk 2010). To quantify these before and after project activities had been initiated, at five hydro stations (see figure 2) community members took daily measurements of the quantity of water (in m³/s) and sediment (in t/d) carried downstream at or close to the point of main water discharge from that micro-watershed. As table 3 illustrates, there was a declining trend in water flow and sediment load overall, though with some variation across stations.

4. Analytical Approach and Results

Results from the DID approach suggest that project-supported SWC activities had significant effects on soil water content and photosynthetic activity, the size of which increases significantly over time. Estimated impacts vary by intervention type and season, although coefficients are difficult to interpret without more specific information on the nature, location, and timing of activities. Analysis of daily volume and sediment content of water flows at hydro-stations in the project area, though less rigorous, suggests that the impacts are not only statistically significant but economically meaningful.

4.1 The Impact of SLM Activities on Vegetation

To assess impacts of SLM interventions on the outcomes of interest, we use a fixed-effects regression model on a geographic discontinuity design from treated micro-watersheds and controls in a 5-km radius of the TWIWRD critical watersheds (see figure 4). Using a panel data set incorporating a baseline period of pre-intervention data, estimates of program impact are based on a DID approach that cancels out any time-invariant differences between treated and control areas. Indexing pixels by i , micro-watersheds by m , season-year combinations by t , and years by y , the specification is

$$Y_{it} = \alpha_i + \lambda_t + \beta T_{my-1} + \gamma R_{it} + e_{it}, \quad (1)$$

where the outcome variable Y_{it} , is the value of the NDVI, SAVI, and LSWI for pixel i at time t ; T_{my-1} is the treatment indicator, defined as the lagged cumulative share of total land affected by the three types of treatment discussed earlier; R_{it} denotes pixel-level rainfall; λ_t is a set of season/year fixed effects; α_i a set of pixel fixed effects; and e_{it} an error term. The parameter of interest is β , the estimated impact of project-led SLM activities.

Results from estimating equation (1), shown in table 4, suggest that, controlling for pixel and time fixed effects, the three types of SWC investment have significant positive impacts on the vegetation indices

considered. All coefficients are very precisely estimated, positive, and highly significant, suggesting that project activities improved soil water content and vegetation cover. Estimated elasticities are highest for SWC on degraded land, followed by SWC on cultivated land, and then tree planting. Information on the marginal cost of specific measures would have allowed us to test how efficiently project resources were allocated. Comparing outcome variables, the largest effects are found for the LSWI, which responds to the project objectives of reducing erosion and improving soil water-holding capacity.

The magnitude of estimated elasticities is comparable to results from similar studies which argue that changes of this size in NDVI are associated with sizeable carbon sequestration that, at commonly assumed carbon values, translate into significant benefits (World Bank 2016). Two factors may impart additional downward bias on our coefficient estimates: First, institution-building and training activities covered the entire river basin rather than just the intervention areas. Anecdotal evidence points towards considerable contamination as the government also supported SLM-related initiatives in the non-project watersheds we used as a control, creating a downward bias. Second, our inability to more precisely locate the areas covered by specific SWC activities suggests that the coefficients in table 4 are averages that conceal possibly vast heterogeneity in terms of treatment type and watershed characteristics. Disaggregated data to more precisely describe the nature of interventions would have made it possible to explore how specific SWC activities affect soil water moisture and vegetation cover in the short and long term. They would also have allowed to assess how these impacts vary with biophysical, socioeconomic, and institutional characteristics in ways that could inform identification of hotspots for SWC intervention and improve understanding of the underlying relationships.

As there is no strong a priori rationale for using a 5 km buffer to define the control area, we explore the robustness of the results to alternative widths by restricting control pixels to fall within 1 and 2-km bands from the treated watershed's boundary. Results from estimating the model based on these buffers in table 5 are very close to those in table 4, suggesting that buffer width has little effect on either the sign or significance of estimated coefficients. Except for LSWI, point estimates increase slightly with buffer size, a finding that would be consistent with the presence of localized spillovers that peter out as one moves further from the treated watersheds' boundary. More precise treatment data would allow to explore this hypothesis and is one of several areas where future research is desirable.

Whether SLM interventions -in Ethiopia and elsewhere- are sustainable in the long term has been the subject of considerable debate (Smit *et al.* 2017). Although too little time has elapsed since the project closed to make any meaningful inferences on long-term effects from the data, we can include additional lags of the treatment variable on the right-hand side of (1) to assess sustainability by using variation in the speed of project roll-out across micro-watersheds -assumed to be random- for identification. Doing so for T_{my-1} and

T_{my-2} with corresponding coefficients β_1 and β_2 allows us to explore if the impacts of SWC structures established a year ago (β_1) are significantly different from those put in place two years ago or longer ($\beta_1 + \beta_2$).

The results reported in Table 6 suggest that, for all the indices considered here, the impact of interventions undertaken two or more years ago is two to three times larger than that of more recent interventions. Variation also emerges between treatment types and outcome indicators: for SWC activity on cultivated land, the immediate impacts on all indices are negative, possibly because establishing new conservation structures requires removal of existing vegetation and time for regrowth. SWC activities on degraded land and new tree plantings, on the other hand, have immediate and positive impacts across the board, with coefficient estimates marginally larger for new tree planting.

While lack of information on the location or timing of interventions makes it difficult to pinpoint the effect of, say, terracing in specific settings so as to tease out heterogeneity in impacts, e.g. by slope or pre-project levels of land degradation, it is possible to assess the extent to which the impacts of different types of treatment vary with time by interacting T_{my-1} with the season in which outcome variables are observed to obtain estimated impacts of SWC activities on the outcomes in different seasons. The resulting coefficients and t-tests for significance of differences between them (table 7) point to inter-seasonal variation in estimated impacts by a factor of two to three.¹⁴ The variation is most pronounced for the LSWI. The type of benefits observed also differs for SWC on cultivated and on degraded land. Together with tree plantings, interventions on cultivated land have the most impact on water-holding capacity and vegetative cover (NDVI/SAVI) in the rainy season, followed by the pre-rainy and the dry seasons. In the dry season the estimated impacts are greatest for SWC activities on degraded land.

4.2 Time Variation and Impacts on Flow and Sediment Load

The modest magnitude of estimated coefficients and the paucity of benchmark estimates in the literature may raise concerns about whether, beyond their statistical significance, the estimated coefficients are economically meaningful in terms of having reduced the amount of runoff and soil erosion. To address this, we used the fact that at five hydrological stations, each located at the point of discharge for a micro-watershed, from 2010 through 2015 daily data were collected on the volume of water flows (in m^3/s) and the amount of sediment they carried (in t/d). Complementing the notation in equation (1) by indexing stations by s and each day in year y by d allowed us to estimate the short-term impact of different types of SWC activities on water flow and sediment load by estimating a regression of the form

$$Y_{sd} = \alpha_s + \lambda_y + \beta T_{my-1} + \sum_{k=0}^3 \gamma_k R_{sd-k} + \varepsilon_{st}, \quad (2)$$

¹⁴ As appendix table 2 illustrates, estimated effects also vary by season and length of treatment.

where Y_{sd} is daily water flow or sediment load for hydro station q on day d of the year; as in equation (1) T_{my-l} is the treatment indicator at the micro-watershed level; R_{id-k} is daily rainfall for day d ; α_s and λ_y are hydro station and year fixed effects; and ε_{st} is the time-varying error component.

A key advantage of equation (2) is that amounts of sediment in downstream water flows directly measure soil erosion, the reduction of which is one of the main objectives of SLM projects. In interpreting the regression results, however, this must be weighed against the limitations imposed by the fact that data are available for only a few stations in intervention areas. Identification thus relies on variation in treatment intensity and results are most appropriately interpreted as indicating correlation rather than causality. Estimates of equation (2) suggest (table 7) that SLM activities on cultivated land, degraded land, and areas planted with new trees are statistically significantly and negatively correlated with daily water flow and sediment load.

Interestingly, in contrast to the earlier results, point estimates are rather large and statistically significantly different from zero. The estimated treatment elasticities of daily water flows at mean values of treatment and outcome indicators are -82%, -44% and -16% for SWC on cultivated land, SWC on degraded land and planting trees, respectively. Treatment indicators are also significantly negatively associated with daily sediment load with estimated elasticities of -158%, -33% and -14% for cultivated land, degraded land and planting trees, respectively. Without reading too much into these figures, they increase confidence that the quantitatively modest, though statistically significant, estimates obtained earlier for LSWI, SAVI, and NDVI are indicative of economically meaningful outcomes.

5. Conclusion and Policy Implications

This study demonstrates that freely available imagery, when combined with information on the location, type, and timing of SWC efforts, offers a new way to assess the impact of these interventions at a scale and resolution superior to what was available in the past, at a fraction of the cost. Applying this methodology to the TBIWRD points towards significant impacts, the magnitude of which was most pronounced for soil water content and which are robust to the choice of differently sized treatment groups. Ground measurement of water flow and sediment content at certain hydrological stations provides independent support to this finding, suggesting that project activities were associated with large reductions in sediment load. Valuing these in economic terms would be an important area for future research that would allow strengthening the economic rationale for such efforts by comparing benefits to the cost of specific interventions.

The fact that we obtain highly significant results, despite limitations due to the high level of aggregation of treatment variables by space, time, and activity type, highlights the potential of remotely sensed data to complement traditional data sources to improve understanding of climate change impacts and ways to

address them at the micro level. Such data can help inform, both retrospectively and for the future, the design and evaluation of interventions such as SWC activities in near real time and at a scale that is more aligned with how such interventions are designed. Treatment data quality, in particular deficiencies in geocoding and disaggregation by type of these data, thus emerges as the main constraint on the ability to use remotely sensed data for more in-depth analysis. For this reason, routine generation of geographically explicit, disaggregated, and clearly documented intervention data is likely to have very high payoffs and offer opportunities for fruitful follow-up research in at least two respects: First, it would allow to assess not only overall impacts but also their variation with initial conditions and over space in near real time and at a scale commensurate with how interventions are normally designed. Moreover, linking remotely sensed vegetation indices to geo-referenced data -based either on surveys at the household- and plot-level or on local readings of climatic variables by community members along the lines reported here or by sensors that may be controlled remotely- offers opportunities to better understand the biophysical correlates and economic meaning of such data, as well as the channels through which they may affect individuals' behavior in response to climate change.

Table 1: Summary Statistics: Characteristics and Treatment Variables for Program Watersheds

Variable	Total	Baskura	Enguli	Enkulal	Kentai	Zefie
Basic characteristics						
Area (ha)	85,702	11,116	29,978	20,113	11,132	13,363
Micro-watersheds (No.)	160	30	40	37	25	28
Elevation (m)		2340	2417	2390	3023	2701
Slope (degrees)		10.0	13.8	8.2	11.3	14.0
Total treated area (ha), 2015						
Soil & water cons. (SWC)	72,634	9,792	26,851	14,376	10,056	11,558
SWC on cultivated land	53,674	7,066	18,990	10,867	7,990	8,762
<i>Percent of total</i>	<i>0.626</i>	<i>0.636</i>	<i>0.633</i>	<i>0.540</i>	<i>0.718</i>	<i>0.656</i>
SWC on degraded land	18,960	2,726	7,862	3,509	2,066	2,796
<i>Percent of total</i>	<i>0.221</i>	<i>0.245</i>	<i>0.262</i>	<i>0.174</i>	<i>0.186</i>	<i>0.209</i>
Area planted w. trees	6,783	1,215	1,565	1,600	905	1,499
<i>Percent of total</i>	<i>0.079</i>	<i>0.109</i>	<i>0.052</i>	<i>0.080</i>	<i>0.081</i>	<i>0.112</i>
Means seasonal rainfall						
Dry season (<i>Bega</i> ; Oct 1 -Jan 31)	123.6	98.3	154.9	108.1	109.0	108.8
Pre-rainy (<i>Kiremt</i> ; Feb 1- May 31)	214.3	168.6	249.5	189.0	218.4	206.8
Rainy season (<i>Belg</i> ; June 1- Sep 30)	1,109.1	1,165.3	1,081.6	1,123.9	1,089.5	1,119.0

Source: Project data.

Table 2: Imagery-based Outcome Variables for Control and Treatment Areas

	NDVI		SAVI		LSWI		Rainfall (mm)	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Dry season (Bega)								
2005-09	0.384	0.388	0.226	0.226	0.110	0.120	116.65	121.65
2009-12	0.387	0.396	0.231	0.234	0.106	0.118	92.71	96.82
2012-16	0.363	0.376	0.211	0.216	0.078	0.094	141.67	146.24
Pre-rainy season (Kiremt)								
2005-09	0.206	0.214	0.123	0.126	-0.015	-0.004	178.46	187.47
2009-12	0.202	0.211	0.121	0.124	-0.019	-0.007	169.81	177.22
2012-16	0.235	0.249	0.141	0.147	-0.009	0.006	264.62	275.89
Rainy season (Belg)								
2005-09	0.476	0.489	0.297	0.305	0.232	0.253	1114.60	1121.44
2009-12	0.529	0.532	0.330	0.331	0.263	0.273	1164.46	1170.19
2012-16	0.464	0.477	0.291	0.299	0.223	0.239	1037.97	1048.21

Source: Calculated from Landsat 7 imagery using GEE.

Note: Mean elevation and slope for control areas are 2,464 mm and 11.28 degrees, and for treatment areas 2,522 m and 11.76 degrees.

Table 3: Daily Water Flow and Sediment Load in Treatment Watersheds

	Total	Enkual	G/Mechaw	Guale	Tikur wu	Toma
Flow in m³/s						
2010	0.339	0.101	0.530	0.404	0.305	0.353
2011	0.213	0.089	0.380	0.097	0.071	0.425
2012	0.160	0.098	0.141	0.167	0.052	0.341
2013	0.201	0.082	0.234	0.163	0.064	0.460
2014	0.277	0.135	0.311	0.026	0.147	0.765
2015	0.253	0.104	0.201	0.110	0.240	0.749
Mean	0.241	0.102	0.300	0.161	0.147	0.516
Daily sediment load in t/d						
2010	2.809	1.731	3.460		2.942	3.104
2011	1.308	0.408	1.858		0.757	2.210
2012	0.882	0.677	0.728		0.476	1.646
2013	0.973	0.619	0.930		0.294	2.049
2014	1.398	0.632	1.079		0.390	3.490
2015	1.380	0.563	0.852		1.368	3.416
Mean	1.458	0.772	1.485		1.038	2.653

Source: Project data.

Table 4: Pixel-level DID Regression to Assess Impact of Soil and Water Conservation Measures on NDVI, SAVI, & LSWI

	SWC on cultivated land	SWC on degraded land	New area planted with trees
Dependent variable NDVI			
Lag treatment	0.00771*** (149.79)	0.03054*** (238.77)	0.04213*** (114.12)
R-squared	0.753	0.753	0.753
Elasticity ^a	0.00503*** (149.79)	0.00717*** (238.77)	0.00245*** (114.12)
Dependent variable SAVI			
Lag treatment	0.00510*** (142.43)	0.01900*** (213.41)	0.02492*** (96.98)
R-squared	0.72	0.721	0.72
Elasticity ^a	0.00555*** (142.43)	0.00744*** (213.41)	0.00242*** (96.98)
Dependent variable LSWI			
Lag treatment	0.00680*** (141.52)	0.02165*** (181.25)	0.05293*** (153.59)
R-squared	0.739	0.739	0.739
Elasticity ^a	0.01489*** (141.52)	0.01706*** (181.25)	0.01035*** (153.59)

Notes: Number of observations: 81,394,215. Treatment is a time-varying variable indicating treatment intensity in the micro-watershed previous year. Mean seasonal rainfall, time-season, and pixel fixed effects are included throughout but not reported. t-statistics are in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

^aTo facilitate comparison of treatment effects, figures presented are elasticities computed as: $\varepsilon_{Y,T} = (\partial Y / \partial T)(\bar{T} / \bar{Y}) = \beta(\bar{T} / \bar{Y})$ where \bar{Y} and \bar{T} are mean values of outcome and treatment indicators for pixels in the TBIWRD treatment micro-watersheds.

Table 5: Robustness Check with Alternative Buffers for Pixel-level DID Regressions

	SWC on cultivated land	SWC on degraded land	New area planted with trees
A. 1-km buffer			
Dependent variable NDVI			
Lag treatment	0.00600*** (92.50)	0.03073*** (196.41)	0.01979*** (46.70)
R-squared	0.752	0.752	0.752
Elasticity ^a	0.00391*** (92.50)	0.00721*** (196.41)	0.00115*** (46.70)
Dep. Var.=SAVI			
Lag treatment	0.00401*** (88.95)	0.01860*** (170.88)	0.00885*** (30.02)
R-squared	0.722	0.722	0.721
Elasticity ^a	0.00437*** (88.95)	0.00728*** (170.88)	0.00086*** (30.02)
Dep. Var.=LSWI			
Lag treatment	0.00642*** (105.65)	0.02166*** (147.71)	0.04372*** (110.13)
R-squared	0.738	0.738	0.738
Elasticity ^a	0.01406*** (105.65)	0.01707*** (147.71)	0.00855*** (110.13)
B. 2-km buffer			
Dep. Var.=NDVI			
Lag treatment	0.00640*** (109.84)	0.02939*** (205.87)	0.02793*** (70.02)
R-squared	0.751	0.752	0.751
Elasticity ^a	0.00417*** (109.84)	0.00690*** (205.87)	0.00163*** (70.02)
Dep. Var.=SAVI			
Lag treatment	0.00435*** (107.28)	0.01817*** (182.94)	0.01519*** (54.75)
R-squared	0.721	0.721	0.721
Elasticity ^a	0.00473*** (107.28)	0.00712*** (182.94)	0.00148*** (54.75)
Dep. Var.=LSWI			
Lag treatment	0.00646*** (118.38)	0.02117*** (158.44)	0.04689*** (125.66)
R-squared	0.738	0.738	0.738
Elasticity ^a	0.01414*** (118.38)	0.01668*** (158.44)	0.00917*** (125.66)

Notes: Number of observations: 38,679,313 and 49,131,115 for the 1-km and 2-km buffers, respectively. Treatment is a time-varying variable indicating treatment intensity in the micro-watershed previous year. Mean seasonal rainfall, time-season, and pixel fixed effects are included throughout but not reported. t-statistics are in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

^aTo facilitate comparison of treatment effects, figures presented are elasticities computed as: $\varepsilon_{Y,T} = (\partial Y / \partial T)(\bar{T} / \bar{Y}) = \beta(\bar{T} / \bar{Y})$ where \bar{Y} and \bar{T} are mean values of outcome and treatment indicators for pixels in the TBIWRD treatment micro-watersheds.

Table 6: NDVI, SAVI, and LSWI - Pixel-level Fixed-effect Estimates of SWC Impact by Length of Treatment

	SWC on cultivated land	SWC on degraded land	New area planted with trees
Dependent variable NDVI			
Treated only one year	-0.01908*** (-114.53)	0.01638*** (62.91)	0.03137*** (40.81)
Treated \geq 2 years	0.01232*** (205.10)	0.03099*** (215.30)	0.05392*** (108.11)
R ²	0.752	0.752	0.752
Dependent variable SAVI			
Treated only one year	-0.01175*** (-101.40)	0.00772*** (42.65)	0.01100*** (20.58)
Treated \geq 2 years	0.00789*** (188.79)	0.01956*** (195.34)	0.03449*** (99.41)
R ²	0.723	0.723	0.723
Dependent variable LSWI			
Treated only one year	-0.00628*** (-40.54)	0.01135*** (46.87)	0.06344*** (88.73)
Treated \geq 2 years	0.00956*** (170.96)	0.02354*** (175.76)	0.05504*** (118.63)
R ²	0.744	0.744	0.744

Notes: Number of observations: 75,018,149; marginal effects are reported. Mean seasonal rainfall, time-season, and pixel fixed-effects included throughout but not reported. t-statistics are in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 7: Pixel-level Fixed-Effect Estimates of SWC Impact by Season

	SWC on cultivated land	SWC on degraded land	New area planted with trees
Dependent variable NDVI			
Lag treatment, dry season, β_1	0.00701*** (97.95)	0.04718*** (257.38)	0.03394*** (62.20)
Lag treatment, pre-rainy, β_2	0.00792*** (110.81)	0.02483*** (135.77)	0.04855*** (89.07)
Lag treatment, main rainy, β_3	0.00828*** (109.52)	0.01770*** (90.30)	0.04417*** (76.01)
R ²	0.753	0.753	0.753
t-test: $\beta_1 = \beta_2$	10.51***	-97.16***	20.77***
t-test: $\beta_1 = \beta_3$	14.11***	-122.53***	13.98***
t-test: $\beta_2 = \beta_3$	4.03***	-29.67***	-5.99***
Dependent variable SAVI			
Lag treatment, dry season, β_1	0.00297*** (59.70)	0.02289*** (179.35)	0.01089*** (28.67)
Lag treatment, pre-rainy, β_2	0.00496*** (99.76)	0.01587*** (124.66)	0.02299*** (60.59)
Lag treatment, main rainy, β_3	0.00773*** (146.76)	0.01814*** (132.91)	0.04347*** (107.47)
R ²	0.721	0.721	0.72
t-test: $\beta_1 = \beta_2$	32.92***	-43.82***	24.70***
t-test: $\beta_1 = \beta_3$	75.44***	-28.39***	63.93***
t-test: $\beta_2 = \beta_3$	43.89***	13.52***	40.21***
Dependent variable LSWI			
Lag treatment, dry season, β_1	0.00675*** (101.01)	0.04662*** (272.38)	0.05053*** (99.21)
Lag treatment, pre-rainy, β_2	0.00408*** (61.21)	0.00265*** (15.49)	0.02682*** (52.72)
Lag treatment, main rainy, β_3	0.01001*** (141.77)	0.01476*** (80.68)	0.08610*** (158.74)
R ²	0.739	0.739	0.739
t-test: $\beta_1 = \beta_2$	-32.82***	-204.72***	-36.08***
t-test: $\beta_1 = \beta_3$	38.64***	-141.80***	52.05***
t-test: $\beta_2 = \beta_3$	70.17***	53.99***	86.79***

Notes: Number of observations: 81,394,215; marginal effects are reported. Mean seasonal rainfall, time-season, and pixel fixed effects are included throughout but not reported. t-statistics are in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 8: Estimated Impact of Different Types of Micro-watershed Treatment on Stream Flows and Sediment Load

	SWC on cultivated land	SWC on degraded land	New area planted with trees
Dependent variable: water flow (m³/s)			
Lag treatment indicator	-0.35022*** (-10.81)	-1.03252*** (-8.13)	-1.26691*** (-5.18)
Daily rainfall	0.01313*** (16.46)	0.01312*** (16.40)	0.01312*** (16.37)
One-day lag daily rainfall	0.00219** (2.71)	0.00219** (2.69)	0.00219** (2.69)
Two-day lag daily rainfall	0.00136 (1.68)	0.00136 (1.67)	0.00136 (1.67)
Three-day lag daily rainfall	0.00064 (0.80)	0.00063 (0.79)	0.00064 (0.79)
R ²	0.065	0.061	0.057
No. of observations	10,204	10,204	10,204
Elasticity ^a	-0.82360*** (-10.81)	-0.44430*** (-8.13)	-0.16006*** (-5.18)
Dependent variable: sediment load (t/d)			
Lag treatment indicator	-3.99966*** (-7.28)	-4.57322*** (-4.92)	-6.44764** (-3.15)
Daily rainfall	0.12495*** (21.11)	0.12476*** (21.04)	0.12462*** (21.00)
One-day lag daily rainfall	0.00622 (1.04)	0.00603 (1.00)	0.0059 (0.98)
Two-day lag daily rainfall	-0.00713 (-1.19)	-0.00732 (-1.22)	-0.00745 (-1.24)
Three-day lag daily rainfall	-0.01129 (-1.91)	-0.0115 (-1.94)	-0.01164* (-1.96)
R ²	0.087	0.084	0.082
No. of observations	8,472	8,472	8,472
Elasticity ^a	-1.57725*** (-7.28)	-0.32999*** (-4.92)	-0.13660** (-3.15)

Notes: Year and micro-watershed fixed effects are included throughout but not reported. t-statistics are in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

^aTo facilitate comparison of treatment effects, figures presented are elasticities computed as: $\varepsilon_{Y,T} = (\partial Y / \partial T)(\bar{T} / \bar{Y}) = \beta(\bar{T} / \bar{Y})$ where \bar{Y} and \bar{T} are mean values of outcome and treatment indicators for pixels in the TBIWRD treatment micro-watersheds.

Figure 1. Sub-watersheds Receiving TBIWRD Investment Support

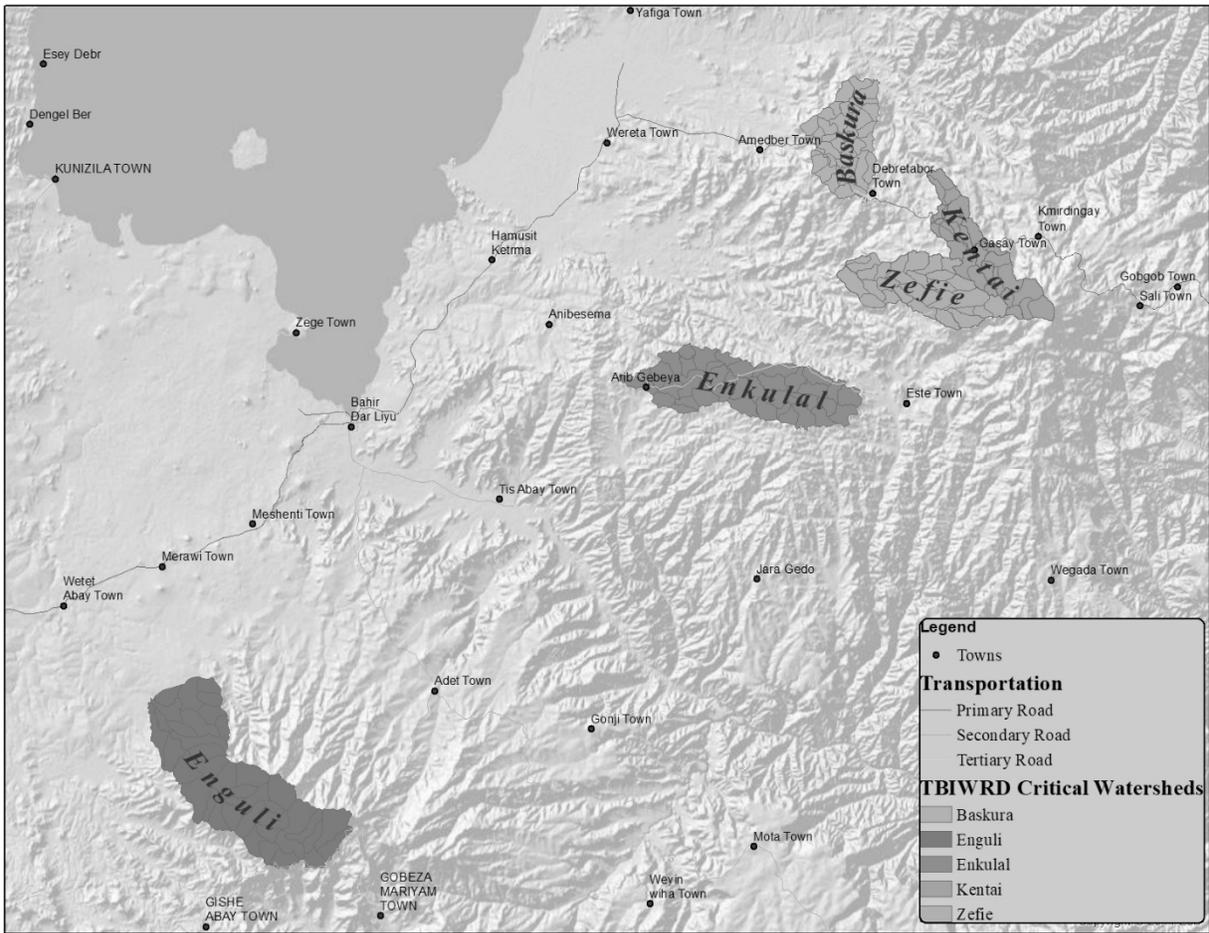


Figure 2. Macro- and Micro-watersheds Analyzed

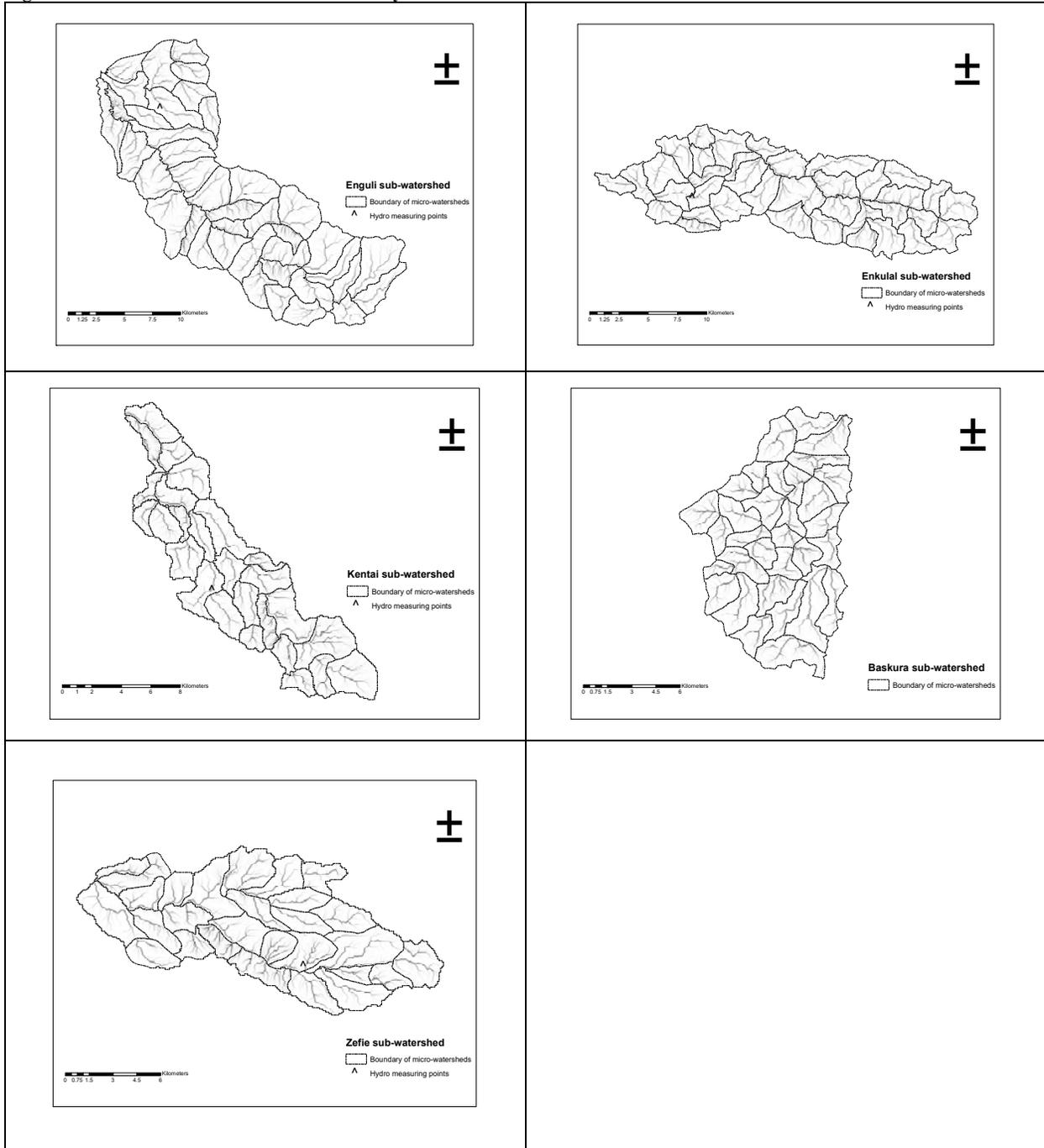


Figure 3. Daily Rainfall in the 5 Hydro-stations Studied

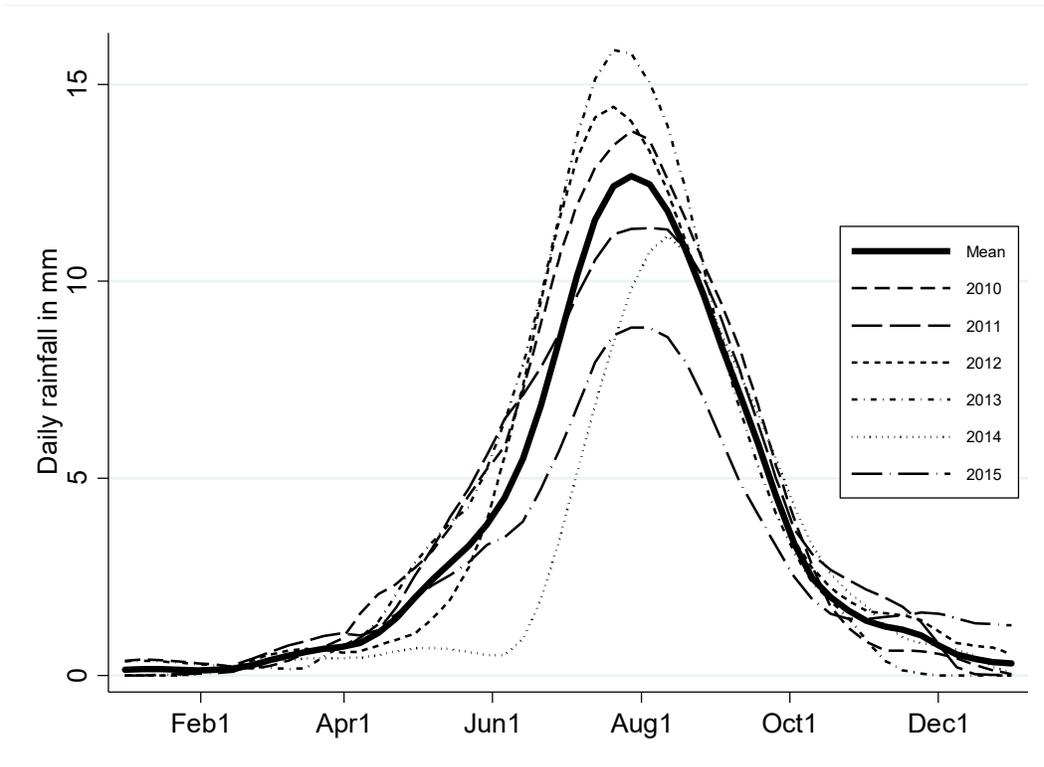


Figure 4. Tana Beles Watersheds with Control Areas (5-km buffer)

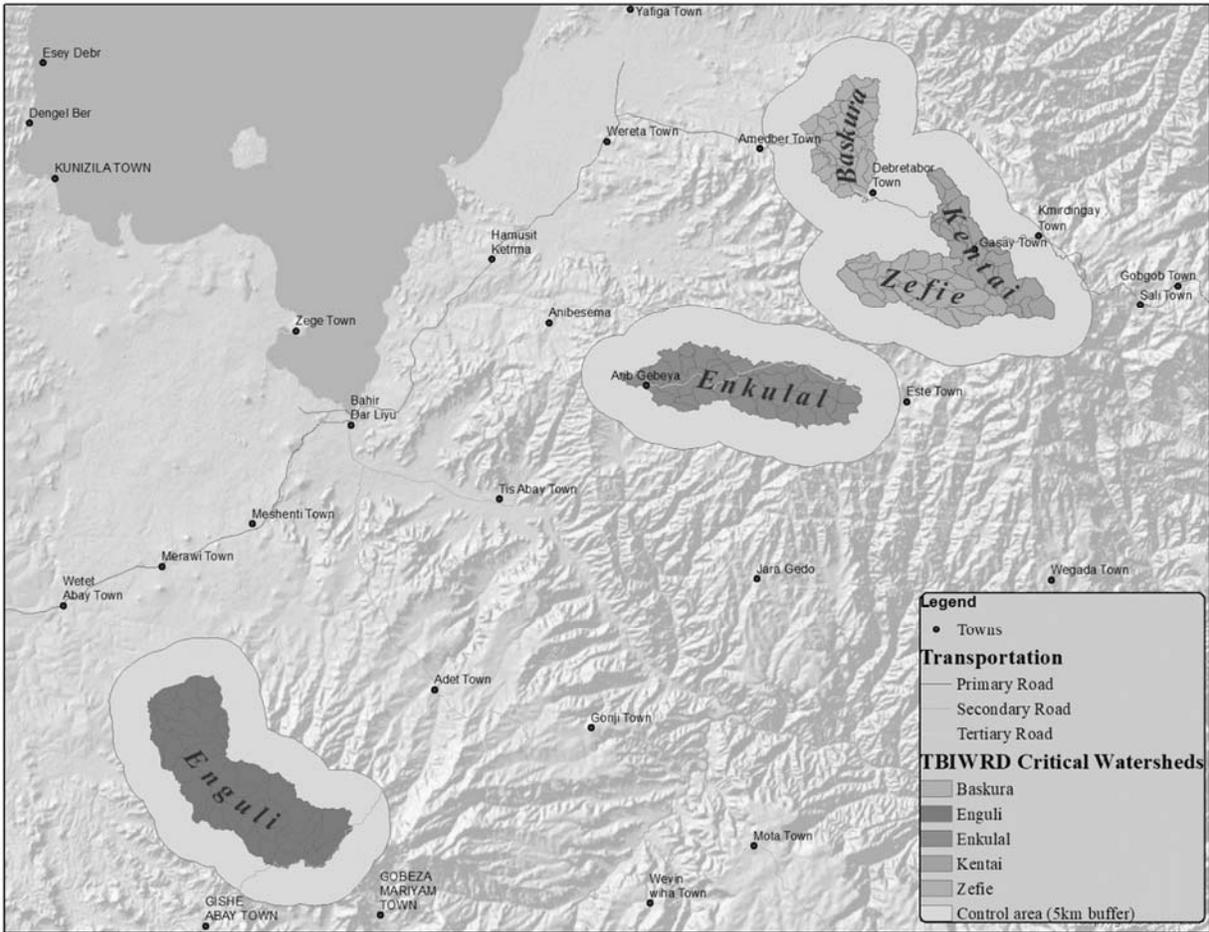
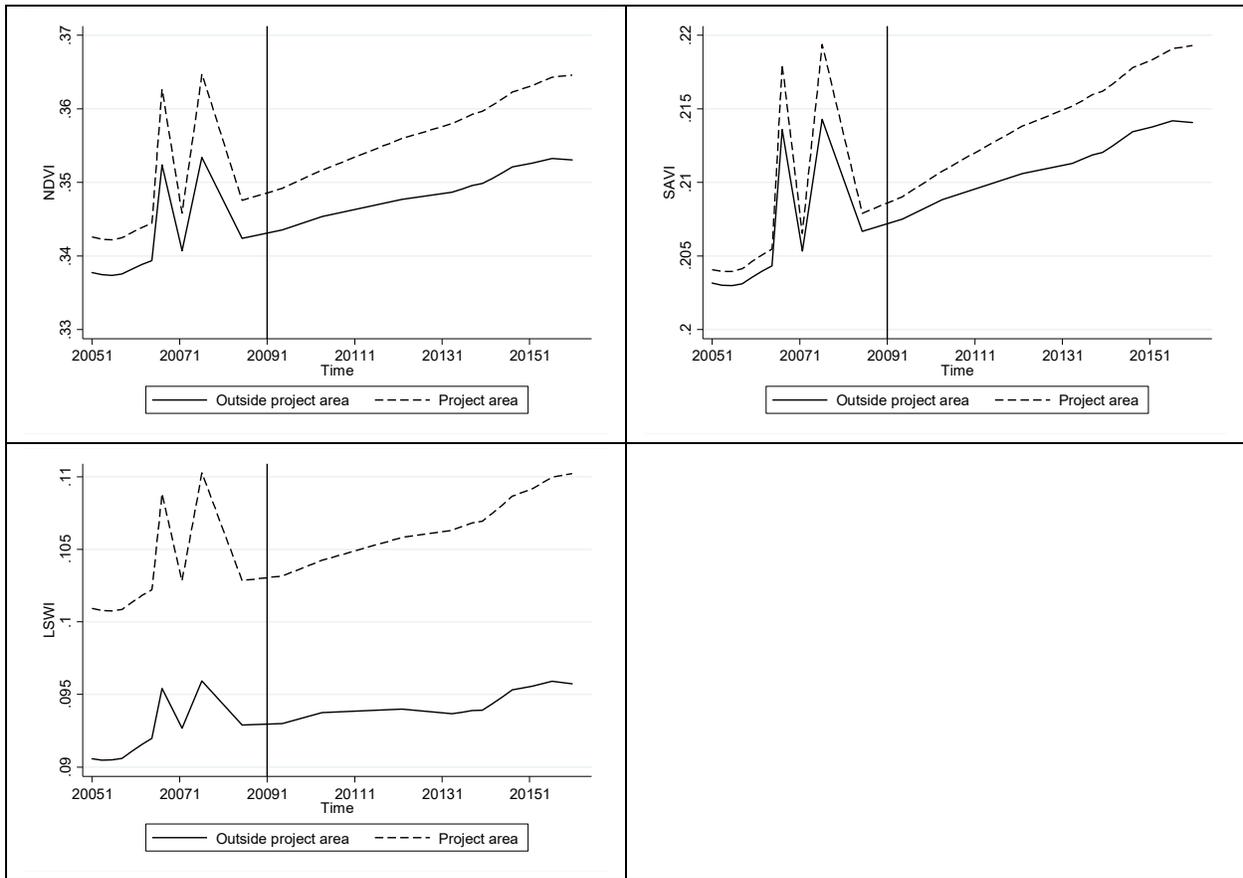


Figure 5. NDVI, SAVI, and LSWI Levels in Project and Control Areas Before and During the Project



Appendix Table 1. Evolution of Treatment Intensity over Time

Variable	Total	Baskura	Enguli	Enkual	Kentai	Zefie
Treatment 2009 (ha)						
Soil & water cons. on cult. land	2,167	330	430	289	640	479
SWC on degraded land	347	0	318	28	1	0
Trees planted	56	0	56	0	0	0
Treatment 2010 (ha)						
Soil & water cons. on cult. land	9,730	1,104	3,047	2,517	1,631	1,429
SWC on degraded land	2,217	124	1,609	333	61	91
Trees planted	335	0	304	5	0	26
Treatment 2011 (ha)						
Soil & water cons. on cult. land	23,441	2,749	8,766	5,384	3,451	3,090
SWC on degraded land	7,405	653	3,425	819	1,422	1,085
Trees planted	945	149	343	113	145	194
Treatment 2012 (ha)						
Soil & water cons. on cult. land	33,379	4,353	11,635	7,438	4,634	5,319
SWC on degraded land	11,155	1,066	5,262	1,297	1,802	1,728
Trees planted	2,221	319	866	427	186	424
Treatment 2013 (ha)						
Soil & water cons. on cult. land	43,378	5,831	15,063	9,301	6,278	6,907
SWC on degraded land	18,434	2,692	7,679	3,349	2,066	2,648
Trees planted	3,466	606	1,177	734	336	613
Treatment 2014 (ha)						
Soil & water cons. on cult. land	48,710	6,507	16,942	10,214	7,369	7,677
SWC on degraded land	18,699	2,714	7,782	3,423	2,066	2,712
Trees planted	5,360	1,059	1,422	1,053	738	1,089
Treatment 2015 (ha)						
Soil & water cons. on cult. land	53,674	7,066	18,990	10,867	7,990	8,762
SWC on degraded land	18,960	2,726	7,862	3,509	2,066	2,796
Trees planted	6,783	1,215	1,565	1,600	905	1,499

Source: Project data.

Appendix Table 2: Pixel-level Fixed-effect Estimates of SWC Impact by Season and Length of Treatment

	SWC on cultivated land	SWC on degraded land	New area planted with trees
Dependent variable NDVI			
Treated only one year: dry season	0.00362*** (14.00)	0.05004*** (122.25)	0.00389** (3.15)
Treated one year: pre-rainy season	-0.00083** (-3.24)	0.00099* (2.43)	0.02235*** (18.12)
Treated only one year: rainy season	-0.07227*** (-248.23)	-0.00825*** (-17.36)	0.07577*** (55.94)
Treated ≥ 2 years: dry season	0.00610*** (67.22)	0.04293*** (202.39)	0.05554*** (71.82)
Treated ≥ 2 years: pre-rainy season	0.00828*** (91.49)	0.02782*** (131.48)	0.06771*** (87.71)
Treated ≥ 2 years: rainy season	0.02539*** (259.06)	0.02104*** (93.54)	0.03568*** (43.25)
R ²	0.753	0.753	0.752
Dependent variable SAVI			
Treated only one year: dry season	-0.00121*** (-6.72)	0.02118*** (74.36)	-0.01688*** (-19.68)
Treated one year: pre-rainy season	-0.00109*** (-6.08)	-0.00116*** (-4.10)	-0.00472*** (-5.50)
Treated only one year: rainy season	-0.03929*** (-193.97)	0.00168*** (5.10)	0.06418*** (68.12)
Treated ≥ 2 years: dry season	0.00278*** (44.03)	0.02083*** (141.12)	0.02733*** (50.80)
Treated ≥ 2 years: pre-rainy season	0.00522*** (82.83)	0.01809*** (122.89)	0.03921*** (73.01)
Treated ≥ 2 years: rainy season	0.01751*** (256.84)	0.01981*** (126.54)	0.03665*** (63.87)
R ²	0.723	0.723	0.723
Dependent variable LSWI			
Treated only one year: dry season	0.00827*** (34.43)	0.03902*** (102.46)	0.03274*** (28.55)
Treated one year: pre-rainy season	-0.00145*** (-6.06)	-0.01242*** (-32.91)	0.00817*** (7.12)
Treated only one year: rainy season	-0.03141*** (-115.93)	0.00663*** (15.00)	0.16813*** (133.44)
Treated ≥ 2 years: dry season	0.00604*** (71.53)	0.04784*** (242.45)	0.06636*** (92.25)
Treated ≥ 2 years: pre-rainy season	0.00509*** (60.45)	0.00599*** (30.45)	0.04298*** (59.85)
Treated ≥ 2 years: rainy season	0.01935*** (212.17)	0.01588*** (75.87)	0.05477*** (71.37)
R ²	0.744	0.744	0.744

Notes: Number of observations is 75,018,149 throughout; marginal effects are reported. Mean seasonal rainfall, time-season and pixel fixed effects are included throughout but not reported. t-statistics are in parenthesis: *** significant at 1%; ** significant at 5%; * significant at 10%.

References

- Adgo, E., A. Teshome, and B. Mati. 2013. "Impacts of Long-Term Soil and Water Conservation on Agricultural Productivity: The Case of Anjenie Watershed, Ethiopia." *Agricultural Water Management*, **117**(Supplement C), 55-61.
- Anderson, M. C., R. G. Allen, A. Morse and W. P. Kustas. 2012. "Use of Landsat Thermal Imagery in Monitoring Evapotranspiration and Managing Water Resources." *Remote Sensing of Environment*, **122**, 50-65.
- Bajgain, R., et al. 2015. "Sensitivity Analysis of Vegetation Indices to Drought over Two Tallgrass Prairie Sites." *ISPRS Journal of Photogrammetry and Remote Sensing*, **108**, 151-160.
- BenYishay, A., S. Heuser, D. Runfola and R. Trichler. 2016. "Indigenous Land Rights and Deforestation: Evidence from the Brazilian Amazon." *AidData Working Paper 22*, College of William and Mary, Williamsburg, VA.
- Boegh, E., et al. 2002. "Airborne Multispectral Data for Quantifying Leaf Area Index, Nitrogen Concentration, and Photosynthetic Efficiency in Agriculture." *Remote Sensing of Environment*, **81**(2), 179-193.
- Chaney, E. 2013. "Revolt on the Nile: Economic Shocks, Religion, and Political Power." *Econometrica*, **81**(5), 2033-2053.
- Chen, Q. 2015. "Climate Shocks, Dynastic Cycles and Nomadic Conquests: Evidence from Historical China." *Oxford Economic Papers*, **67**(2), 185-204.
- Costinot, A., D. Donaldson and C. Smith. 2016. "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World." *Journal of Political Economy*, **124**(1), 205-248.
- Dell, M., B. F. Jones and B. A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, **4**(3), 66-95.
- Dinkelman, T. 2015. "Long Run Health Repercussions of Drought Shocks: Evidence from South African Homelands." National Bureau of Economic Research, Inc, NBER Working Papers: 21440.
- Ekbohm, A. 2008. "Determinants of Soil Capital." Resources For the Future, Discussion Papers.
- Ethiopia National Meteorological Agency. 2017. Seasonal Forecast. http://www.ethiomet.gov.et/other_forecasts/seasonal_forecast
- Gao, X., A. R. Huete, W. Ni and T. Miura. 2000. "Optical–Biophysical Relationships of Vegetation Spectra without Background Contamination." *Remote Sensing of Environment*, **74**(3), 609-620.
- Farr et al. 2007. "The Shuttle Radar Topography Mission." *Review of Geophysics*, **45**(2), RG2004.
- Gebreselassie, S., O. K. Kirui and A. Mirzabaev. 2016. "Economics of Land Degradation and Improvement in Ethiopia." in E. Nkonya, et al. (eds.), *Economics of Land Degradation and Improvement – a Global Assessment for Sustainable Development*, Springer International Publishing, Cham.
- Gilabert, M. A., J. González-Piqueras, F. J. García-Haro and J. Meliá. 2002. "A Generalized Soil-Adjusted Vegetation Index." *Remote Sensing of Environment*, **82**(2), 303-310.
- Gollin, D., R. Jedwab and D. Vollrath. 2013. "Urbanization with and without Industrialization." Department of Economics, University of Houston, Working Papers: 2013-290-26.
- Gómez, C., J. C. White and M. A. Wulder. 2016. "Optical Remotely Sensed Time Series Data for Land Cover Classification: A Review." *ISPRS Journal of Photogrammetry and Remote Sensing*, **116**, 55-72.
- Groppo, V. and K. Kraehnert. 2016. "Extreme Weather Events and Child Height: Evidence from Mongolia." *World Development*, **86**, 59-78.
- Hansen, M. C., et al. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science*, **342**(6160), 850.
- Hansen, M. C., et al. 2016. "Mapping Tree Height Distributions in Sub-Saharan Africa Using Landsat 7 and 8 Data." *Remote Sensing of Environment*, **185**, 221-232.
- Henderson, J. V., A. Storeygard and U. Deichmann. 2017. "Has Climate Change Driven Urbanization in Africa?" *Journal of Development Economics*, **124**, 60-82.
- Herweg, K. 1996. "Field Manual for Assessment of Current Erosion Damage.", Bern: University of Bern
- Huete, A., et al. 2002. "Overview of the Radiometric and Biophysical Performance of the Modis Vegetation Indices." *Remote Sensing of Environment*, **83**(1), 195-213.
- Huete, A. R. 1988. "A Soil-Adjusted Vegetation Index (Savi)." *Remote Sensing of Environment*, **25**(3), 295-309.
- Huete, A. R., H. Q. Liu, K. Batchily and W. van Leeuwen. 1997. "A Comparison of Vegetation Indices over a Global Set of Tm Images for Eos-Modis." *Remote Sensing of Environment*, **59**(3), 440-451.
- Irons, J. R., J. L. Dwyer and J. A. Barsi. 2012. "The Next Landsat Satellite: The Landsat Data Continuity Mission." *Remote Sensing of Environment*, **122**, 11-21.
- Jia, R. 2014. "Weather Shocks, Sweet Potatoes and Peasant Revolts in Historical China." *Economic Journal*, **124**(575), 92-118.
- Justice, C. O., et al. 1998. "The Moderate Resolution Imaging Spectroradiometer (Modis): Land Remote Sensing for Global Change Research." *IEEE Transactions on Geoscience and Remote Sensing*, **36**(4), 1228-1249.
- Kassie, M., et al. 2008. "Estimating Returns to Soil Conservation Adoption in the Northern Ethiopian Highlands." *Agricultural Economics*, **38**(2), 213-232.
- Kung, J. K.-S. and Y. Bai. 2011. "Induced Institutional Change or Transaction Costs? The Economic Logic of Land Reallocations in Chinese Agriculture." *Journal of Development Studies*, **47**(10), 1510-1528.
- Lybbert, T. J., A. Smith and D. A. Sumner. 2014. "Weather Shocks and Inter-Hemispheric Supply Responses: Implications for Climate Change Effects on Global Food Markets." *Climate Change Economics*, **5**(4), 1-11.

- Markham, B. L. and D. L. Helder. 2012. "Forty-Year Calibrated Record of Earth-Reflected Radiance from Landsat: A Review." *Remote Sensing of Environment*, **122**, 30-40.
- Maurel, M. and M. Tuccio. 2016. "Climate Instability, Urbanisation and International Migration." *Journal of Development Studies*, **52**(5), 735-752.
- Maystadt, J.-F. and O. Ecker. 2014. "Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks?" *American Journal of Agricultural Economics*, **96**(4), 1157-1182.
- Melesse, M. B. and E. Bulte. 2015. "Does Land Registration and Certification Boost Farm Productivity? Evidence from Ethiopia." *Agricultural Economics*, **46**(6), 757-768.
- Myneni, R. B., et al. 2002. "Global Products of Vegetation Leaf Area and Fraction Absorbed Par from Year One of Modis Data." *Remote Sensing of Environment*, **83**(1), 214-231.
- Naidoo, R., M. Trent and A. Tomasek. 2009. "Economic Benefits of Standing Forests in the Highland Areas of Borneo: Quantification and Policy Analysis." *Conservation Letters*, **2**(1), 35-44.
- Nkonya, E., et al. 2016. "Global Cost of Land Degradation." in E. Nkonya, et al. (eds.), *Economics of Land Degradation and Improvement – a Global Assessment for Sustainable Development*, Springer International Publishing, Cham.
- Qi, J., et al. 1994. "A Modified Soil Adjusted Vegetation Index." *Remote Sensing of Environment*, **48**(2), 119-126.
- Reed, B. C., M. D. Schwartz and X. Xiao. 2009. "Remote Sensing Phenology: Status and the Way Forward." in A. Noormets (ed.), *Phenology of Ecosystem Processes: Applications in Global Change Research*, Springer New York, New York, NY.
- Sakamoto, T., et al. 2007. "Detecting Temporal Changes in the Extent of Annual Flooding within the Cambodia and the Vietnamese Mekong Delta from Modis Time-Series Imagery." *Remote Sensing of Environment*, **109**(3), 295-313.
- Schmidt, E. and B. Zemaadim. 2015. "Expanding Sustainable Land Management in Ethiopia: Scenarios for Improved Agricultural Water Management in the Blue Nile." *Agricultural Water Management*, **158**(Supplement C), 166-178.
- Schmidt, E., P. Chinowsky, S. Robinson and K. Strzepek. 2017. "Determinants and Impact of Sustainable Land Management (Slm) Investments: A Systems Evaluation in the Blue Nile Basin, Ethiopia." *Agricultural Economics*, **48**(5), 613-627.
- Schmidt, E. and F. Tadesse. 2017. "The Sustainable Land Management Program in the Ethiopian Highlands: An Evaluation of Its Impact on Crop Production." *ESSP Working Paper 103*, Ethiopian Development Research Institute and International Food Policy Research Institute, Addis Ababa.
- Schott, J. R., et al. 2012. "Thermal Infrared Radiometric Calibration of the Entire Landsat 4, 5, and 7 Archive (1982–2010)." *Remote Sensing of Environment*, **122**, 41-49.
- Semmens, K. A., et al. 2016. "Monitoring Daily Evapotranspiration over Two California Vineyards Using Landsat 8 in a Multi-Sensor Data Fusion Approach." *Remote Sensing of Environment*, **185**, 155-170.
- Shiferaw, B. and S. Holden. 1999. "Soil Erosion and Smallholders' Conservation Decisions in the Highlands of Ethiopia." *World Development*, **27**(4), 739-752.
- Smit, H., R. Mucbe, R. Ahlers and P. van der Zaag. 2017. "The Political Morphology of Drainage--How Gully Formation Links to State Formation in the Choke Mountains of Ethiopia." *World Development*, **98**, 231-244.
- Tadesse, L., K. V. Suryabhagavan, G. Sridhar and G. Legesse. 2017. "Land Use and Land Cover Changes and Soil Erosion in Yezat Watershed, North Western Ethiopia." *International Soil and Water Conservation Research*, **5**(2), 85-94.
- Tamene, L., Z. Adimassu, E. Aynekulu and T. Yaekob. 2017. "Estimating Landscape Susceptibility to Soil Erosion Using a Gis-Based Approach in Northern Ethiopia." *International Soil and Water Conservation Research*, **5**(3), 221-230.
- Tefera, B. and G. Sterk. 2010. "Land Management, Erosion Problems and Soil and Water Conservation in Fincha'a Watershed, Western Ethiopia." *Land Use Policy*, **27**(4), 1027-1037.
- Tesfaye, A. and R. Brouwer. 2012. "Testing Participation Constraints in Contract Design for Sustainable Soil Conservation in Ethiopia." *Ecological Economics*, **73**(1), 168-178.
- Tesfaye, A., R. Brouwer, P. van der Zaag and W. Negatu. 2016. "Assessing the Costs and Benefits of Improved Land Management Practices in Three Watershed Areas in Ethiopia." *International Soil and Water Conservation Research*, **4**(1), 20-29.
- Tiwari, S., H. G. Jacoby and E. Skoufias. 2017. "Monsoon Babies: Rainfall Shocks and Child Nutrition in Nepal." *Economic Development and Cultural Change*, **65**(2), 167-188.
- Tucker, C. J. 1979. "Red and Photographic Infrared Linear Combinations for Monitoring Vegetation." *Remote Sensing of Environment*, **8**(2), 127-150.
- Venables, A. J. 2017. "Breaking into Tradables: Urban Form and Urban Function in a Developing City." *Journal of Urban Economics*, **98**, 88-97.
- Villa, K. M. and L. E. Bevis. 2017. "Intergenerational Transmission of Health, Cognition and Non-Cognitive Skills in Cebu, Philippines", *Paper presented at the 2017 Annual AAEA Meetings American Applied Economics Association*, Chicago, IL.
- World_Bank. 2016. "Value for Money Analysis for the Land Degradation Projects of the Gef." *Paper presented at the 51st GEF Council Meeting*, Global Environment Facility, Washington DC.
- World_Bank. 2017. "Fighting Land Degradation at Landscape Scale: Sustainable Land and Water Management in Africa's Drylands and Vulnerable Landscapes." in E. a. N. M. G. Practice (ed.), Washington DC.
- Wossen, T., T. Berger and S. Di Falco. 2015. "Social Capital, Risk Preference and Adoption of Improved Farm Land Management Practices in Ethiopia." *Agricultural Economics*, **46**(1), 81-97.

- Wulder, M. A., et al. 2012. "Opening the Archive: How Free Data Has Enabled the Science and Monitoring Promise of Landsat." *Remote Sensing of Environment*, **122**, 2-10.
- Xiao, X., et al. 2002. "Characterization of Forest Types in Northeastern China, Using Multi-Temporal Spot-4 Vegetation Sensor Data." *Remote Sensing of Environment*, **82**(2), 335-348.
- Xiao, X., et al. 2003. "Sensitivity of Vegetation Indices to Atmospheric Aerosols: Continental-Scale Observations in Northern Asia." *Remote Sensing of Environment*, **84**(3), 385-392.
- Xiao, X., et al. 2009. "Land Surface Phenology: Convergence of Satellite and Co2 Eddy Flux Observations." in A. Noormets (ed.), *Phenology of Ecosystem Processes: Applications in Global Change Research*, Springer New York, New York, NY.
- Zhu, Z. and C. E. Woodcock. 2012. "Object-Based Cloud and Cloud Shadow Detection in Landsat Imagery." *Remote Sensing of Environment*, **118**(Supplement C), 83-94.
- Zhu, Z. and C. E. Woodcock. 2014. "Automated Cloud, Cloud Shadow, and Snow Detection in Multitemporal Landsat Data: An Algorithm Designed Specifically for Monitoring Land Cover Change." *Remote Sensing of Environment*, **152**, 217-234.
- Zhu, Z., S. Wang and C. E. Woodcock. 2015. "Improvement and Expansion of the Fmask Algorithm: Cloud, Cloud Shadow, and Snow Detection for Landsats 4-7, 8, and Sentinel 2 Images." *Remote Sensing of Environment*, **159**, 269-277.