Using Satellite Images to Measure Crop Productivity: Long-Term Impact Assessment of a Randomized Technology Adoption Program in the Dominican Republic

by Lina Salazar, Ana Palacios, Michael Selvaraj, and Frank Montenegro

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Abstract:

This study combines three rounds of surveys with remote sensing information to measure long-term impacts of a program that promoted modern irrigation systems among small and medium landholders in the Dominican Republic (PATCA). Specifically, Landsat 7 and Landsat 8 satellite images are used to measure the causal effects of the PATCA program on agricultural productivity, measured through vegetation indices (NDVI and OSAVI). To this end, 377 plots were analyzed (129 treated and 248 controls) for the period from 2011 to 2019. The PATCA program was implemented using a randomized control trial (RCT). Hence, this study follows a Difference-in-Differences (DD) and Event study methodology to capture the program's effects. The results confirmed that program beneficiaries have higher vegetation indices, and therefore experienced a higher productivity throughout the post-treatment period. Also, there is some evidence of spillover effects to neighboring farmers. Furthermore, the Event Study model shows that productivity impacts are obtained in the third year after the adoption takes place. These findings suggest that the process of adopting irrigation technologies can be long and complex as it requires time to generate productivity impacts. In a more general sense, this study reveals the great potential that exists in combining field data with remote sensing information to assess long-term impacts of agricultural programs on agricultural productivity.

JEL Codes: Q00, Q120, Q160

Keywords: Irrigation, Remote Sensing, Impact Evaluation, Agriculture

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1. Introduction

The agricultural sector faces the triple challenge of increasing food production to maintain a growing population, protecting natural resources and adapting to climate change. To achieve this goal, agricultural technologies that aim to foster productivity must be promoted to increase food production without expanding the agricultural frontier to areas with high ecological, biological and cultural value. To this end, several countries in Latin America and the Caribbean have implemented several agricultural policies that aim to increase productivity through technology adoption including irrigation, post-harvest technologies, soil conservation technologies, etc. (Maffioli et al., 2008; Flores et al., 2014; Gonzalez et al., 2009; Lopez and Salazar, 2017; Gonzalez-Flores and Le Pommellec, 2019).

Modern irrigation is a technological change that has the potential to successfully meets this triple challenge. As a result of these technologies, greater production can be obtained while increasing water use efficiency and adaptation to climate change. In fact, adoption of modern irrigation improves climate change adaptation by reducing farmers' dependence on rainy seasons, allowing longer windows for planting, and harvesting.

An important example in the region is the Program for the Support of Innovation in Agricultural Technology II (*PATCA* for its acronym in Spanish). This program was implemented in the Dominican Republic between 2012 and 2015 by the Ministry of Agriculture to promote the use of several technologies that included modern irrigation[5]). The program was implemented using a two-stage randomization at the levels of subregions and producers. First, subregions were randomly assigned into treatment and second, producers located in selected subregions were assigned into treatment. In 2015, an impact evaluation of the program was conducted to determine the short-term effects of program participation on productivity for the irrigation and

[5] Other technologies included mulching, and-leveling, green-houses, post-harvest management equipment, and improved pastures

improve pastures technologies using two rounds of surveys that provided abundant socio-economic and productive information (Aramburu et al., 2019). The results show that farmers who received improved pastures increased agricultural income while beneficiary farmers who received modern irrigation technologies experienced lower value of production during the 2014 agricultural cycle. When analyzing the impacts based on the number of exposure intensity (i.e. months using the irrigation technology), the authors found evidence of changes in the farmers' crop portfolios suggesting a shift from annual to perennial crops. These findings indicated that the process of adoption had not yet resulted into productivity effects due to changes in the production systems. Hence, further analysis was needed to understand what appeared to be a long-term process.

In fact, it is well established in the literature that agricultural technology adoption is a process that requires time, capital and knowledge. Hence, to understand this process might require several survey rounds to capture the time frame required for productivity impacts to develop and monitor farmers' progress. However, while agricultural household surveys are a rich source of information, these are costly and involve complex field logistics limiting the periodicity of data collection (USAID, 2019). Then, agricultural surveys depict a picture at a specific moment in time that might leaving behind important information needed to understand the complexity of technological adoption.

This paper aims to address this gap, using information from remote sensing technologies to obtain a more accurate description of the dynamics behind the irrigation adoption process. Specifically, we use satellite imagery to construct vegetation indexes, as a proxy for productivity, that fill out the data gaps between different survey rounds collected for the purpose of evaluating the PATCA program. For this purpose, we used georeferenced records for 377 plots and 283 farmers to estimate vegetation indices using Landsat 7 and 8 satellite images. Next, trend detection (Mann Kendal) and continuous change detection (CCDC) models were estimated using these vegetation indices to identify trend changes in land coverage. This suggests that farmers altered their productive systems. Subsequently, these vegetation indices, calculated for each plot for the period between 2011 and 2019, were used to measure the impact of the *PATCA* program on productivity. This was implemented by comparing beneficiary and non-beneficiary plots through the Difference-in-Differences and Event Study methodologies.

This study confirms the complementarity between data obtained through remote sensors (i.e. remote sensing) and field data. We find that, in general, the beneficiary plots reported higher vegetative indices in the post-treatment period compared to the control group. This implies healthier crops, with greater vigor and therefore, greater productivity than the control group. Additionally, when we look at the dynamics of the vegetation indices over time, the results show that the benefits from adopting irrigation technologies are obtained three years after the implementation of the technology. However, the coefficients of the subsequent periods are not significant, suggesting that control farmers could have *catched-up* by adopting the technology. In addition, the results present some evidence of indirect impacts in neighboring farmers.

To the best of our knowledge, this would be the first attempt to combine remote sensing information with a randomized design to measure the long-term effects of a program that promotes modern irrigation technologies in the LAC region. By doing so, we aim to illustrate the potential that exists by combining survey data with remote sensing information in order to measure and monitor the effectiveness of technological programs. Overall, this study shows how remote sensing combined with field data can be a valuable tool to measure the dynamic effects of agricultural interventions that seek to promote productivity through technological adoption.

The rest of this paper is organized as follows: Section 2 provides a literature review on the utilization of remote sensing and vegetation indices in agriculture followed by a description of the PATCA II program in Section 3. Next, Section 4 describes the data cleaning process and the construction of vegetation indexes while Section 5 explains the methodologies used for the analysis. Finally, Section 6 presents the results and Section 7 provides the main conclusions of the paper.

2. Literature Review

Over the years, technological advances have been implemented to facilitate the measurement of indicators related to agricultural activity. One of the most important refers to remote sensing (RS) technologies. According to Martos et al., (2021), the application of RS is indispensable for a highly productive and sustainable agriculture. In fact, the authors state that artificial intelligence and cloud computing, applied to agricultural remote sensing, is the fifth agricultural revolution.

Remote sensing can be crucial in decision-making as it combines useful information from multiple sources to detect or assess factors that encourage or limit agricultural production, such as vegetative vigor, and plants' nutritional status. Specifically, remote sensing with external sensors, such as drones or satellites, can be useful to monitor land and crops over time. These instruments allow us to scan crops (Brizuela et al., 2007) and capture different vegetation variables such as health, production, phenological stage or nutritional deficit (Melchiori OPet al., 2008), occupying a central position in precision agriculture and soil studies (Martos et al., 2021). Likewise, remote sensing can be used to measure the spatial variation of productivity, to estimate biomass and agricultural yields, and to obtain samples of physical and chemical properties of vegetation in complex biophysical environments (Aguilar Rivera, 2015). For instance, yields can be accurately predicted by using drones (Maimaitijian et al., (2020); Jian et al., (2020)).

As mentioned in Martos et al., (2021), first studies on RS were focused on the reflection mechanism, absorption, and diffusion of light rays from plant leaves. However, in the last decades, the RS technology has been completely revolutionized. Current studies are related to designing novel algorithms, improving sensor technology and the incorporation of artificial intelligence. The application of these novel technologies has been accompanied by a significant boom in academic articles that discuss and compare different aspects of their implementation, highlight their various applications, underline some of their limitations and identify some of the opportunities in this field (Martos et al., 2021). This paper focused on the latter. Specifically, we aim to highlight the opportunity of RS technologies for the monitoring and evaluation of agricultural programs. In particular, we aim to highlight the role of satellite imagery as a cost-effective tool to complement field data.

The increasing access to satellite images has created a high number of academic research in the field of economics. Donaldson et al. (2016) offer a comprehensive description of the applications of satellite images on this social science. Night-time light data have been used as a proxy for economic activity (under the assumption that lighting is a normal good) within cities (Harari 2016; Storeygard 2016); ethnic homelands (Michalopoulos and Papaioannou 2013, 2014), subnational administrative units (Hodler and Raschky 2014), larger uniform grid squares (Henderson, Squires, Storeygard, and Weil 2016), among others.

Also, climate data collected through sparce weather stations has been combined with remotely sourced readings to estimate measures of interest in a more accurate manner. Kudamatsu et al. (2016) match weather data from RS to the DHS surveys in all 28 African countries to investigate the extent to which infant mortality in Africa is related to weather variation. Satellite imagery has also been used in several studies to estimate the impacts of flooding (Guiteras, Jina, and Mobarak 2015) and cyclones (Yang 2008; Hsiang and Jina 2014), as well as an innovative source of variation to predict colonial settlement patterns using wind speed and direction (Feyrer and Sacerdote 2009).

More specifically, Donaldson et al. (2016) highlight the great number of applications of satellite data in agriculture. For example, using satellite data, Duflo and Pande (2007) estimate the effects of dams in India, which are used for both irrigation and hydropower. The authors argue that dams' locations determined their effectivity. In fact, dams are more likely to be efficient when they are built in locations in which the course of a river is neither too shallow nor steep. For this purpose, they identified the locations using a digital elevation model. Also, Foster and Rosenzweig (2003) combined satellite data with village-level survey data to investigate forest cover changes in India. They find that forest growth was likely caused by an increase in the demand for forest products.

Another application of RS in agricultural economics has been for estimation of production possibility frontiers. Agronomic models such as GAEZ use the characteristics of the location (from a remotely digital elevation model) and crop as modeling inputs. This enables researchers to predict the yield for a given crop in a specific location. Costinot et al. (2016) use that method to predict global agricultural production possibility frontier. Then, they use pixel-by-pixel changes to complement a general equilibrium model of world agricultural trade to estimate that climate change can be expected to reduce global agricultural output by one-sixth. Other studies that used GAEZ models are Nunn and Quian (2011), who study the impact of the discovery of the potato in the New World on European living standards; and Alesina et al. (2013), who argue that today's gender roles are determined by traditional agricultural practices such as the use of the plough.

An additional functionality from remote sensing technologies in agriculture is the estimation of vegetation indices through satellite images to determine crops health dynamics over time (Isla and López, 2005; Militino et al., 2020; Naito et al., 2017; Selvaraj et al., 2020). The most widely used index is the Normalized Difference Vegetation Index (NDVI). In general, the relationship between NDVI values and plant health is directly proportional, which implies that a higher NDVI value is related to better plant health (Chuvieco, 1991). One of the main advantages of using vegetation indexes is that these can be used to analyze specific crops (Moriondo et al., 2007) or to analyze several crops using a homogenous measure (Groten, 2007; Genovese et al., 2001).

The literature provides several examples through which vegetation indices are used to measure productivity. For instance, Selvaraj et al., (2020), calculate vegetation indices over time to estimate the growth dynamics of cassava and to measure crop yields in Colombia. Also, Wang, et al., (2002) found a strong relationship between the NDVI index and forest tree productivity variables, the latter measured using field surveys collected in the Great Plains in the United States. In the case of Carrilla et al., (2013) they use the Enhanced Vegetation Index (EVI) and the tree ring width as measures to estimate changes in plant productivity in high-altitude ecosystems in northern Argentina and southeastern Bolivia. Similarly, Gamon et al. (2013) study the relationship between early snowmelt and vegetation productivity in the Arctic region. They use the NDVI index as an indicator of phenology and vegetation productivity to find that early snowmelt is not related to increased productivity, although it is related to precipitation levels and soil moisture. However, as stated by Donaldson et al. (2016), one downside of using vegetation indexes as a proxy for agricultural productivity is that remote sensors capture greenness increase, which may include the growth of other non-agricultural plants which are not relevant when measuring agricultural productivity. To avoid this issue, NDVI data can be combined with land-use classification that identifies cropland or with field surveys. An example of that is Farmaha et al., (2016) who made some improvements in the measure of remotely sensed yield measurements.

Furthermore, using vegetation indexes has allowed to identify correlations between productivity and variables such as poverty. For example, Sedda et al., (2015) construct vegetation indices to analyze the correlation between poverty, undernourishment, and vegetation level in West Africa. They found an inverse relationship between poverty and the NDVI index, implying that areas with lower vegetation index, and therefore, lower agricultural productivity, face higher levels of poverty. Likewise, Johnson and Brown (2014) found a positive correlation between nutrition and NDVI, in areas with a high levels NDVI dispersion in West Africa. However, in other areas, such as in Ghana, large portions of vegetation are associated with higher risk of child mortality. This is mainly because these areas are located on the edge of urban settlements where populations face more vulnerable conditions (Weeks et al., 2012).

Vegetation indices calculated through satellite imagery have also been used to identify areas with greater or lesser access to irrigation. In this sense, Magidi et al., (2021), use the Sentinel 2 and Landsat 8 satellites to construct the NDVI index. They aim to differentiate between irrigated and dry land areas of smallholders in South Africa, using a machine learning model for classification. With these outcomes, the authors were able to identify differentiated water use patterns between farmers with and without irrigation technology.

The application of RS technology in the literature of impact evaluation of agricultural programs has been more limited. One example is Jayachandran et al. (2016) who used bespoke satellite images (instead of public images) to measure the impact on deforestation of a payment-for-ecosystem services program in Indonesia. To our knowledge, in the case of Latin America, nor impact evaluations of randomized agricultural projects have used satellite images to measure the program's effects on productivity.

Overall, the literature presents a broad arrangement of studies that implemented different applications of RS data in agriculture. However, little research has been done to portray the potential of using RS data on the impact evaluation literature of agricultural projects. This paper aims to contribute to the literature by combining data from satellite images with plot-level survey data to calculate vegetation indexes in order to measure the causal effects of an irrigation program in agricultural productivity.

3. *PATCA:* (Support Program for the Competitive Agrifood Transition)

The Dominican Republic is a country in the Caribbean located at 18 ° 28′35 ″ N 69 ° 53′36 ″ W (Figure 3). It has an area of 48,442 km2 that contains 32 provinces and is surrounded by the Atlantic Ocean except to the west, where it borders with Haiti. Its climatic conditions are typical of countries near the tropics with abundant rains and temperatures between 25 and 35 C. The rainy season runs from April to November, but May, August and September are the most humid months. The driest part of the country is found in the northwest, where it can experience up to six months without any precipitation.

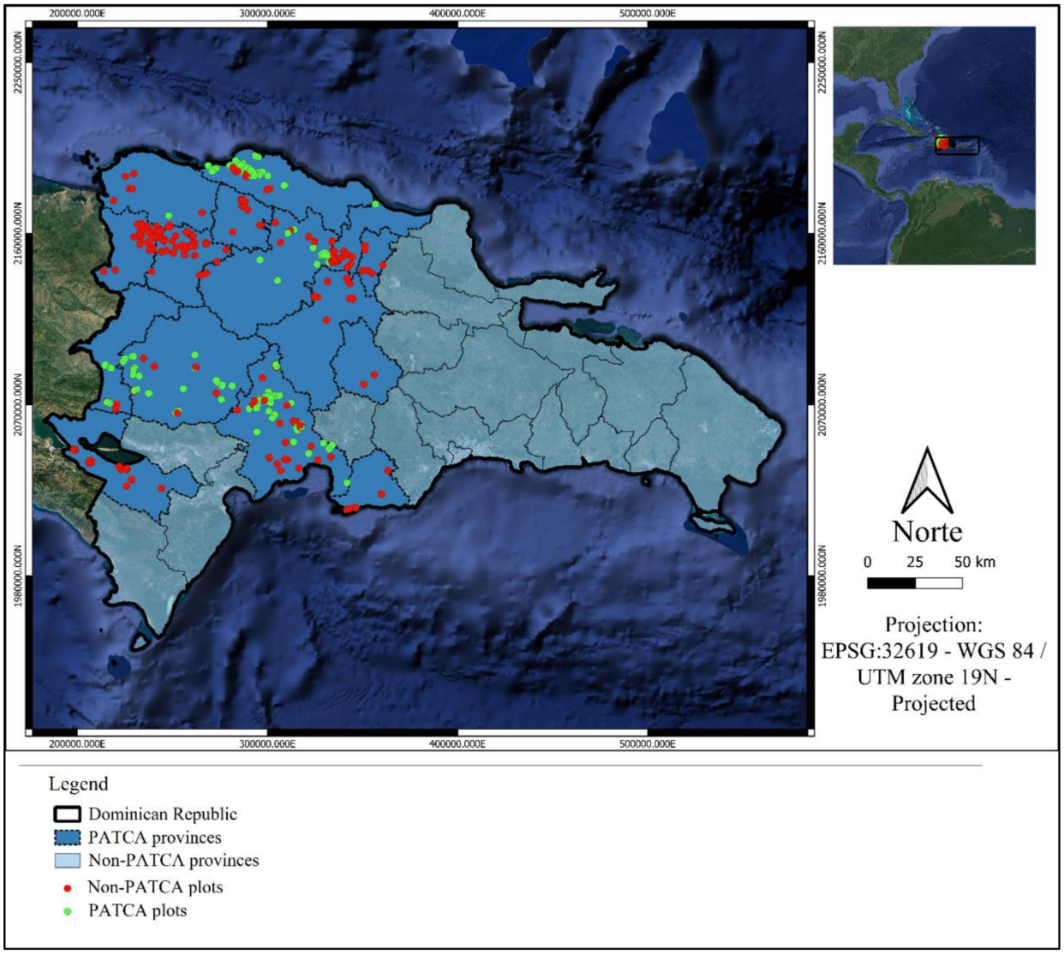
The *PATCA* program was implemented in The Dominican Republic from 2012 to 2014. It aimed to improve agricultural productivity and income of beneficiary farmers by promoting the adoption of agricultural technologies. Following a national registration process where farmers identify the technology of their choice and provided proof of the eligibility, a random group of smallholder farmers were selected to receive a non-reimbursable voucher that financed up to 60% of the total cost of the agricultural technology selected by the farmer (Aramburú et al., 2019).

The randomization process was implemented in two stages. The first stage randomly assigned geographical subzones to treatment and control groups. The second stage randomly selected a group of beneficiary farmers within the group of beneficiary subzones. This process divided the universe of registered farmers into three groups: pure control group (i.e. farmers located in the control subzones), direct beneficiaries (i.e. beneficiary farmers located in treated subzones) and contaminated counterfactual (i.e. non beneficiary farmers located in control subzones). In addition, the date of entry to the program was also randomized among the beneficiary subzones. This allowed us to assure comparability between *PATCA* beneficiaries and the pure control group to conduct an experimental impact assessment. Moreover, comparing contaminated counterfactual with the pure control group allow us to measure spillover effects. In this study we will focus only on the sample of beneficiary farmers who received modern irrigation technologies with their corresponding control group.

Overall, the program targeted producers who meet the following eligibility criteria: (i) be a citizen of the Dominican Republic with a valid identification card (*cedula*); (ii) have legal proof of land tenure; (iii) have agricultural or livestock production as the main economic activity; (iv) be a smallholder farmer; and (v) present evidence of the ability to cover the remaining cost of the technology. Beneficiaries were randomized among farmers who met these requirements and participated in the registration process. Subsequently, due to budgetary constraints during the implementation phase, the program`s geographical scope was limited to only two regions: North and Southwest. By May of 2014, a total of 487 farmers had received the technology, 340 received improved pastures and 147 received irrigation.

As part of the assessment strategy, three rounds of agricultural surveys were conducted: a baseline in 2011, a first follow-up survey in 2014, and a final survey in 2019. These surveys contained detailed information on agricultural and livestock production, land allocation, inputs use, household socio-economic characteristics, income sources, food security, social capital, migration, among others. Also, in 2011, georeferenced information was collected for each of the plots of the beneficiary and control farmers. Overall, a total of 435 of the georeferenced plots (314 producers), that requested irrigation technology were followed over time. Finally, after cleaning data for outliers and missing information (to be described in Section 3), our analysis will focus on 377 parcels (248 treated and 129 control) from 282 smallholder farmers. Figure 1 shows the georeferenced points for the beneficiary and control plots to be analyzed.

Figure 1. Beneficiary and Control Plots



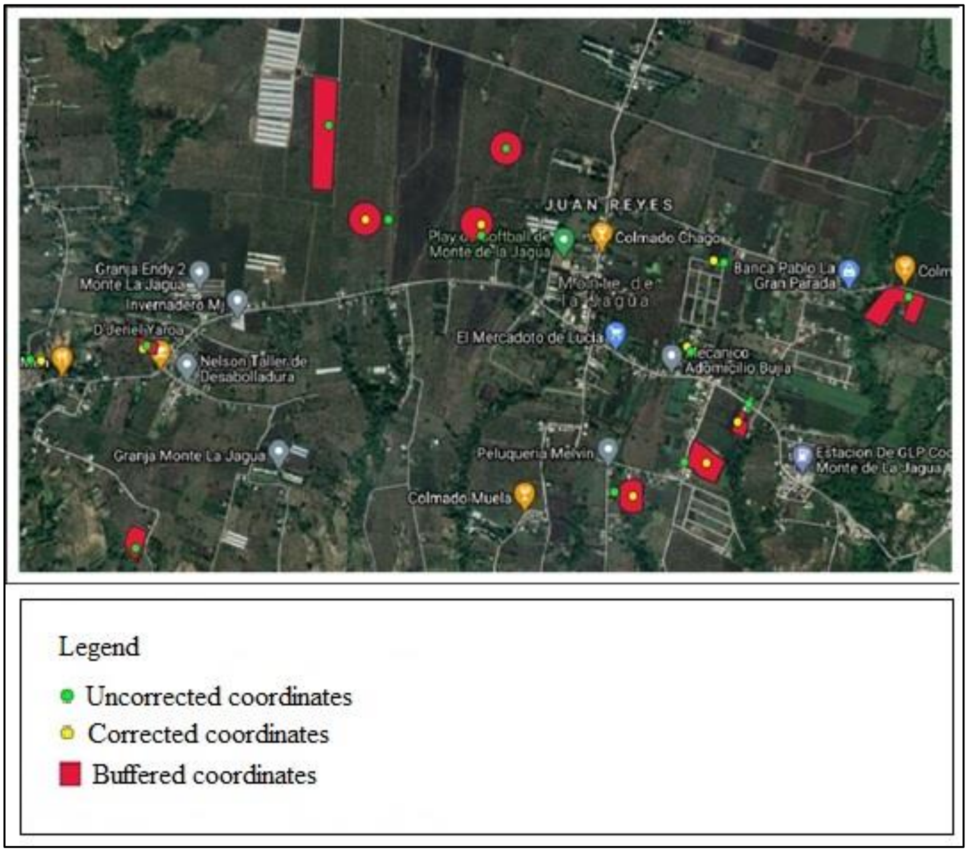
4. Data Description

4.1 Satellite Image Data Cleaning Process

To obtain plot information using satellite images, some previous steps were considered to verify the suitability of the georeferenced points. We provide a detailed description of the process in this section.

The first step is to verify data to avoid erroneous cases. Correction of geographic data consists of visual verification to avoid poorly georeferenced points, such as those found on roads, buildings, trees or field corners as shown in Figure 2 (green dots).

Figure. 2: Description of point correction and creation of buffer and / or polygons



After verifying the GPS points of the 435 geo-referenced plots, we found that 100 points were correctly georeferenced (22.99% of the total) (i.e. yellow dots in Figure 2) while 247 points (65%) had to be manually corrected as they were located on roads, houses, or trees near the plots. This correction was based on information collected in the field surveys (i.e. crop type, plot size, etc.). Further, a 70 meters buffer was drawn to create a polygon for each parcel (i.e., red polygons in Figure 2). However, we detected that 83 of the polygons (23%) contained trees, buildings or roads that could affect the measurement of the vegetation indices. These areas are identified as disturbed areas. Finally, 58 points (13.33%) corresponded to plots with an area of less than 1 hectare of land and were discarded since they did not allow for an adequate extraction of characteristics (i.e., points without buffer or polygons in Figure 2). Overall, the final database contains 377 points or plots to be analyzed (Table 1). From these points, 129 plots correspond to PATCA beneficiaries, and 248 plots correspond to the control group (Table 2).

Corrections could have been avoided if GPS coordinates had been collected carefully, following an established protocol. Specifically, it is important that GPS points are collected in the middle of the plot to avoid manual corrections. If possible, to improve precision, it is recommended to collect GPS location pertaining to all the corners of the parcel.

Table 1: Points correction

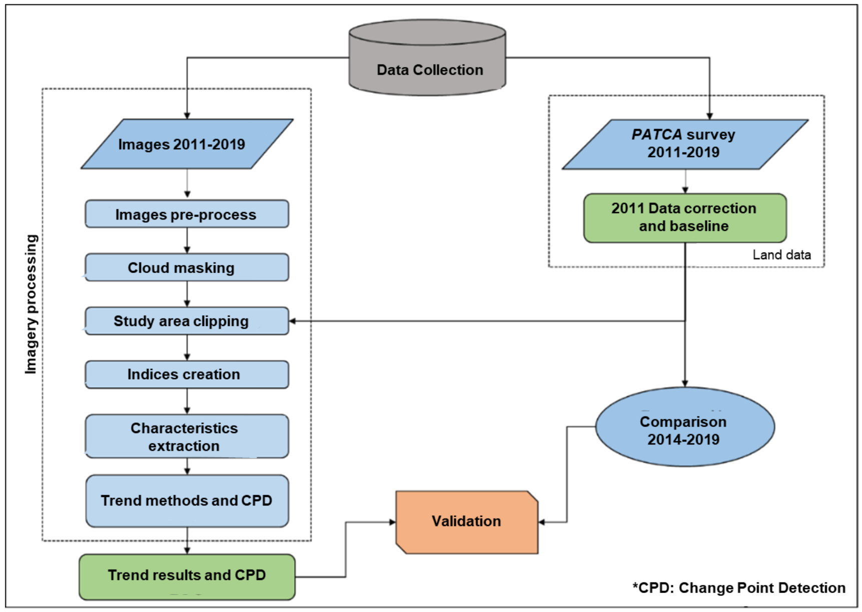
Type of correction	N points	Percentage	Sum N points
Optimal conditions	100	22.99	112
Review based on the type of crop	12	2.76	12
Moved	181	41.61	293
Disturbed areas	15	3.45	308
It was moved and it was in disturbed areas	69	15.86	377
Areas of less than 1 Ha (discarded from the analysis)	58	13.33	435

Table 2: Final Sample

PATCA	N plots / points	Percentage
0	248	65.78
1	129	34.21
Total	377	100.00

The next step corresponds to the Landsat image processing. This consist of downloading and correcting images, cloud masking, and finally creating vegetation indices. Figure 3 describes the process.

Figure 3: Workflow



4.1.1. Landsat images 2011-2019

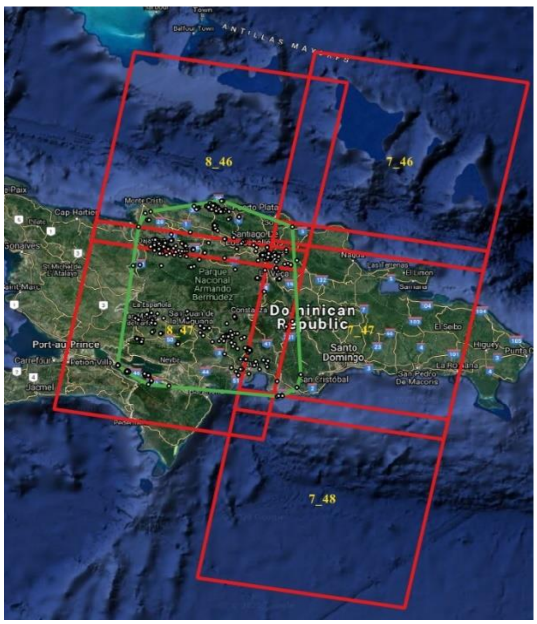
The Landsat program is a series of Earth-observing satellites, jointly managed by the USGS and NASA, that provides the longest continuous space-based record of Earth's land in existence. The first satellite called Landsat 1 was launched on July 23, 1972. To date, there were eight Landsat missions but only the Landsat 7 and 8 missions are currently operative. Unfortunately, due to a failure presented by the Landsat 7 sensor, since 2002, the Scan Line Corrector (SLC) satellite images started to be generated. This failure causes a data loss of at least 22% in all captured images. The two satellites have a spatial and temporal resolution of 30 meters and 16 days, respectively (USGS, 2011).

For this study, Landsat images were collected for the years from 2011 to 2019[6], with a total of 5 images that captured all the georeferenced points (Figure 4). To allow for interpretation, each image must comply with less than 30% of cover clouds (USGS, 2016). Overall, 882 Landsat images were collected from all Landsat satellites (7/8), with 23.8% of the images gathered from

[6] Landsat images of pre-collection 1 for 2 path / 3 row (path 7 / row 46-48 and path 8 / row 46,47; Fig. 5)

Landsat 7 (210) and 76.2% from Landsat 8 (672) as shown in Figure 7. This is because Landsat 7 satellite was only available from 2011 to 2012, while Landsat 8 was available from 2013 to 2019. The average number of images was 73.5 per year for each georeferenced point (Figure 4). Previous studies suggest that at least 10-12 images per year are necessary to generate a reliable trend. Once the Landsat images were compiled, they were pre-processed with the geometric and atmospheric corrections for each image (Chuvieco, 1991). Clouds and cloud shadows were removed using the CFMask (C Mask Function) algorithm (Foga et al., 2017).

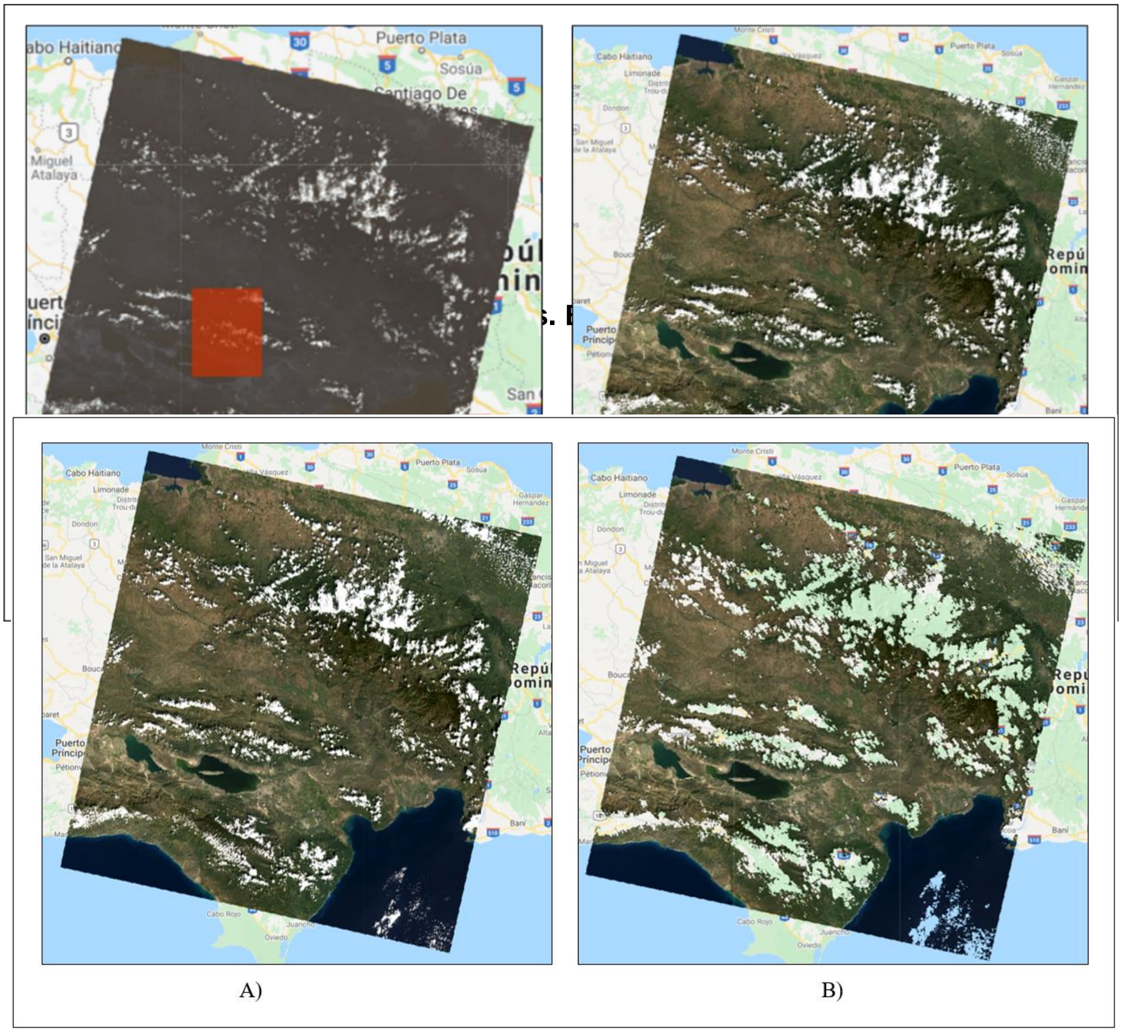
Figure 4: Images for the study area



4.1.2. Atmospheric corrections

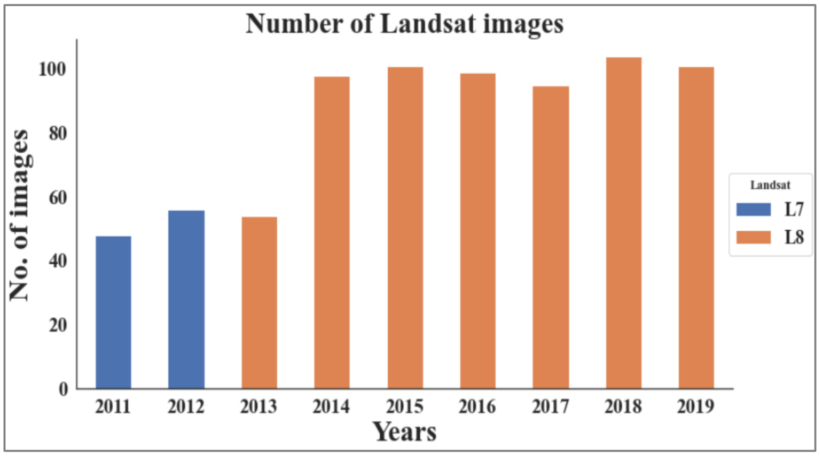
A total of 1080 images were obtained from the Landsat satellites (7/8) for the area of analysis during the 9 years of the study. Next, an image radiometric correction was conducted (Figure 5), followed by the cloud masking process (Figure 6)

Figure 5: A) Uncorrected Landsat image B) Corrected Landsat image



As a result of the corrections made due to reflectance and cloudiness, a total of 882 images were available for the 9 years of analysis, which are divided into 210 Landsat 7 ETM+ images, and 672 Landsat 8 OLI images (Figure 7). Finally, using the corrected and cloud-free images we constructed vegetation indices for each polygon which allowed us to plot and analyze time trends.

Figure 7: Landsat Images per Year



4.1.3. Vegetation indices

Biophysical and biochemical information of the plants are necessary to monitor the nutritional status and vigor of vegetation. This information provides photosynthetic capacity indicators, which are useful information in order to estimate the plant's health.

Vegetation experiences photosynthesis processes, which contain pigments called photosystems with chlorophyll content. Chlorophyll feeds on electromagnetic energy, especially wavelengths that are displayed in the blue and red band of the spectrum (Taiz and Zeiger, 2002). For this reason, we observe that most of the vegetation is green when reflecting this spectral band. Multispectral data (satellite images) can determine these biophysical and biochemical variables, using and developing statistical models known as spectral indices. The spectral indices capture vegetation development and aim to determine the reflectivity variations in the plants using combinations between different spectral bands, avoiding the use of destructive and invasive methods (Gomez Escobar, 2015).

In fact, vegetation indices are the result of the addition, division, subtraction, or multiplication of spectral values. These are quantitative measurements based on the spectral response to obtain physical parameters of a crop such as biomass or chlorophyll. The Normalized Difference

Vegetation Index (NDVI) is one of the most used indices in most plant analysis studies, which allows to identify the change in green biomass, chlorophyll content and water stress (Murillo et al., 2013). In addition to the NDVI, literature has registered different indices for the detection of specific biophysical aspects and the characterization of the plant structure. Thus, for each georeferenced point (i.e. each plot), two vegetation indices were calculated: the Normalized Difference Vegetation Index (NDVI) and the Optimized Soil Adjusted Vegetation Index (OSAVI). We monitor them over time from 2011 to 2019.

NDVI

The Normalized Difference Vegetation Index, also known as NDVI, is a vegetation index that is widely used to estimate the quantity, quality and development of vegetation based on the measurement of the radiation intensity of certain bands of the electromagnetic spectrum that vegetation emits or reflects (Chuvieco, 2008). This indicator is estimated as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Where: *NIR* is the near-infrared band and *RED* is the red band for satellites.

The NDVI is commonly used to estimate plant health status, predict agricultural production, and monitor droughts and areas in the process of desertification. In addition, NDVI has been incorporated into agricultural applications (such as crop monitoring) to facilitate crop exploration and provide precision measures for application of fertilizer and irrigation.

OSAVI

Optimized Soil Adjusted Vegetation Index (OSAVI) shows a slight variation with respect to the traditional NDVI to avoid distortions in the analysis when vegetation is on bare soil. The OSAVI index is rather adapted to studies of vegetation analysis in early growth stages or sparse vegetation. In general, OSAVI can be an appropriate alternative for areas with low plant density and where the soil surface exposure is relevant (Huete et al., 1992; Rondeaux et al., 1996). This indicator is estimated as follows:

$$OSAVI = \left(\frac{NIR - RED}{NIR + RED + L}\right) * (1 + L)$$

Where: *NIR* is the near-infrared band and *RED* is the red band for satellites. In this case, the *L* factor is an adjustment factor for reducing soil presence through values between 0 (for areas with high plant density) and 1 (for areas with low plant density). Rondeaux et al., (1996) explained more thorough the criteria for vegetation density and the value to choose, 0.16 is the *L* value suggested by the authors being the value used in this study.

4.2. Descriptive Statistics

To provide a better understanding of the context, table 3 presents the socio-economic and productive characteristics of the 282 farmers and their 377 plots, for the baseline year (2011). The surveyed farmers are, on average, 53 years old, 10% are female, and have 8 years of education on average. Also, the average household is composed by 3.9 members. Comparing the characteristics of farmers between treatment and control, not statistically significant differences were found between these groups in 2011.

The second part of the table presents the characteristics of the plots. On average, the analyzed plots area is 5.3 hectares, with an average production value of 2,224 USD per hectare. The vegetation index (NDVI), which ranges from 0 to 1, was on average equal to 0.58, with a minimum value of 0.34 and a maximum of 0.83. Comparing control and treated groups at the baseline, we observe no significant differences between the vegetation index of both groups, although some significant differences are observed in terms of the plot area and value of production.

Table 3: Descriptive characteristics of producers and plots

	General				Control		Treatment		*Diff*
Variable	N	Mean	Min	Max	N	Mean	N	Mean	
Producer characteristics (2011)									
Age	282	53.28	23	90	182	52.80	100	54.16	-1.36
		(12.92)							
Gender	282	0.90	0	1	182	0.91	100	0.88	0.03
		(0.29)							
N household members	282	3.98	1	10	182	3.99	100	3.96	0.03
		(1.82)							
Years of education	282	8.22	0	18	182	8.04	100	8.54	-0.50
		(5.25)							
Illiteracy (0.1)	282	0.09	0	1	182	0.10	100	0.07	0.03
		(0.29)							
Plot characteristics (2011)									
NDVI	377	0.58	0.34	0.83	248	0.58	129	0.59	-0.01
		(0.08)							
OSAVI	377	0.40	0.25	0.56	248	0.40	129	0.40	0.01
Plot area	377	5.28	0.31	88.03	248	5.94	129	4.01	1.93**
		(8.24)							
Production value USD / has	377	2224.44	0	21113	248	1965.71	129	2721.8	-756.11**
		(3201.41)							

Notes: Description of the producers and plots characteristics during the period in absence of treatment (2011). Standard deviations in parentheses.

Likewise, Table 4 presents the distribution of the plots (points) analyzed in this study, at the provincial level. Most of the parcels are located in the province of Azua (17%), followed by the province of Puerto Plata (15%), Dajabón (14%) and Santiago Rodríguez (11%). Another group of parcels are located in the province of San Juan, Independencia, Santiago and Espaillat (9%, 7%, 6% and 5%, respectively). Lastly, the rest of the plots are distributed among the provinces of Elias Piña, La Vega, Monte Cristi, Peravia, Hermanas Mirabal, Valverde and Monseñor Nouel. In general, the plots are widely distributed across the country.

Table 4: Distribution of plots by province

Province	N	%
Azua	65	17.24
Dajabon	52	13.79
Elias Pina	8	2.12
Espaillat	22	5.84
Independencia	30	7.96
La Vega	9	2.39
Monte Cristi	7	1.86
Peravia	6	1.59
Puerto Plata	60	15.92
Hermanas Mirabal	4	1.06
San Juan	34	9.02
Santiago	23	6.1
Santiago Rodriguez	43	11.41
Valverde	12	3.18
Monseñor Nouel	2	0.53
Total	**377**	**100**

5. Methodology

In this section, we describe the methodology applied to detect changes in land use trends as well as the methodology to measure the causal impact of the program, using the estimated vegetation indices as proxy variables for productivity.

5.1 Methodologies applied for detecting trends and breaking points in land coverage.

The following is a description of the Mann Kendall and CCDC methods for determining trends and detecting breaking points in vegetation indices.

Mann-Kendall

The Mann-Kendall trend test is one of the most common methods in the literature, and it is mainly applied to detect an increasing or decreasing trend in a particular data set. The test is based on the standard deviation (S). Specifically, each pair of observed values yi, yj (i> j) of the analyzed variable (i.e. vegetation indices) is inspected to find when yi> yj or yi <yj. If the number of positive pairs is P, and the number of the type of negative pairs is M, then S is defined as S = P - M. For n> 10, a Z statistic that follows the standard normal distribution can be defined, with null hypothesis of H_0 = there is no trend and the alternative that is H_1 = there is a trend with a certain significance degree. Then Z is defined as:

$$Z = \begin{cases} \dfrac{S-1}{\sigma_s} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{\sigma_s} & if\ S < 0 \end{cases}$$

$$\sigma_s = \sqrt{\frac{n(n-1)(2n+5)}{18}}$$

(Abdul Aziz and Burn, 2006; Kahya and Kalayci, 2004; van Belle and Hughes, 1984; Yue et al., 2002).

Continuous Change Detection and Classification (CCDC)

The algorithm for continuous change detection and classification (CCDC) is also adequate for detecting a high number of land cover changes, as new images are collected, and land cover maps are provided for any given time. A two-step algorithm is used to mask clouds, cloud shadows, and to eliminate "noisy" observations. CCDC uses a harmonic time series model with components of seasonality, trends, breaking points of surface reflectance, and brightness temperature. The time series model is dynamically updated with new observations. Due to differences in spectral response for various types of land cover changes, the CCDC algorithm uses a threshold derived from the seven Landsat bands. When the difference between the observed and predicted images exceeds a threshold for three consecutive times, a pixel is identified as a land use change (Zhu and Woodcock, 2014).

5.2 Methodology to estimate the program effects on productivity.

As stated above, the main objective of this study is to identify the effect of *PATCA* (focused on irrigation technologies) on agricultural productivity, using vegetation indices as proxy variables. To measure the general effects of the program throughout the post-treatment period when all beneficiaries received the technology, a Difference-in-Differences model is applied as follows:

Equation #1

$$\mathrm{Y_{it}} = \alpha + \gamma \mathrm{Post_t} + \delta(\mathrm{Post} \times \mathrm{Patca})_{\mathrm{it}} + \beta_{\mathrm{i}} + \beta_{\mathrm{t}} + \varepsilon_{\mathrm{it}}$$

Where the dependent variable Y_{it} represents the vegetation indices (i.e. NDVI index and OSAVI index); $Post_t$ is a dummy variable that takes a value of 1 in all the post-treatment periods (periods after the year of 2014, when all beneficiaries have received the technology), and 0 for pre-treatment periods (i.e. 2011-2014); $Patca_{it}$, a dummy variable that takes the value of 1 for plots that belong to beneficiary farmers; $(Post \times Patca)_{it}$ is an interaction variable; β_i is a vector of fixed effects to control for time invariant characteristics at the plot level; β_t annual fixed effects to control for annual events/national policies that equally affect all parcels (i.e. economic growth, fiscal policies, trade policies, etc.); and ε_{it}, is the error term.

To capture the dynamic nature associated to the process of technological adoption, we exploited a methodology known as Event-study, following Miller et al., (2019). For this purpose, we estimate the following equation:

Equation #2

$$Y_{it} = Patca_i \times \sum_{\substack{y=-3 \\ y\neq -1}}^{7} \beta_y \, I\,(t - t_i^* = y) + \beta_i + \beta_t + \varepsilon_{it}$$

The dependent variable, Y_{it}, refers to the vegetation indices. However, in this case, the interaction term differs from the one presented in Equation #1. Specifically, the indicator variable $I(t - t_i^* = y)$ measures the relative time to the year when the technology was implemented (t_i^*) in plot *i* for all treated plots and takes a value of 0 in all periods for non-treated plots. In other words, I is an indicator variable that captures the time elapsed since the technology is applied. Notice that all the farmers had implemented the technology by 2014, however, some received it in 2012 and others in 2013. Hence, this indicator allows us to capture the intensity of the treatment by plot and to identify the period(s) when productivity effects start to develop. That is, this indicator varies for each plot, depending on the year when it received the technology. The omitted category is $\mathrm{y} = -1$, the year before the plot received the technology. Thus, each estimate of the vector β_y is interpreted as the change in the vegetation indices between treated and control plots during the year y, as measured from the year prior to treatment. Notice that, as the date of entry to the program was randomly assigned, this variable is exogenous. Therefore, this methodology allows us to take advantage of the gradual nature of the program roll out. Equation (2) is estimated using a linear regression model and we report the heteroskedasticity-robust standard errors, clustered at the plot level.

This methodology also allows to test comparability between the control and treatment groups in the pre-treatment periods. This assumption is known in the literature as Parallel Trend Assumption and it has an essential role in the validity of the outcomes. This implies that, had program not been in place, the behavior of control and treatment groups should have been similar. Thus, this assumption ensures that the control group is comparable to the treatment group because, in the absence of the program, they would have followed a similar trend. For this case, if the vegetation indices for the treatment and control groups had similar trends before receiving the technology, it is expected that the coefficients associated with temporary events $y = -3$ to $y = -1$ should be small and not statistically significant.

6. Results

6.1 Results on land use trend changes.

Graph Analysis: Vegetation Indices

As previously stated, using the corrected and cloud-free images, we constructed vegetation indices for each of the images and polygons. This allowed us to graph time trends that are displayed in Figure 8 and Figure 9. In Figure 8 we present specific examples for beneficiary and non-beneficiary plots while Figure 9 portrays the aggregate analysis of the NDVI values for treatment and control groups.

As an example, in Figure 8 A and B show two specific cases of farmers who received irrigation technology through *PATCA*, while Figure 8 C corresponds to a plot without *PATCA*. In this figure, the timeframe from 2011 to 2019 is represented on the X axis and the values for the vegetation indices are presented on the Y axis. Additionally, we have a "temporary" variable that takes the value of 0 if the plot reported to have a permanent crop and takes the value of 1 if the plot reported to have a temporary crop.

Figure 8A shows stable vegetation indices values for the year 2011 since it is a fallow plot, as reported in the survey. Then, two peaks and plunges of the vegetation indices in a single year suggest the existence of a temporary crop, for 2012 and 2013. At the beginning of 2014, a low index value increasing throughout the year and reaching its maximum peak at the end of 2014 was observed, confirming what was reported in the survey, indicating the presence of a permanent crop (banana plantation). The values of the indices then decreased throughout 2015.

At the beginning of 2016, the indices increased again following a stable trend between the end of 2016 and mid 2018 (a total of two years of stability), suggesting the presence of a permanent crop. The second semester of 2018 starts with a drop until 2019 where we can notice the behavior associated with a short-cycle temporary crop: an increasing phase, a peak, and a sudden drop within the same year. This result was also confirmed by the second follow-up survey in 2019, which recorded a temporary crop by the end of 2019.

Fig. 8: Vegetation indices time series. A and B) change of temporality, C) permanent crop

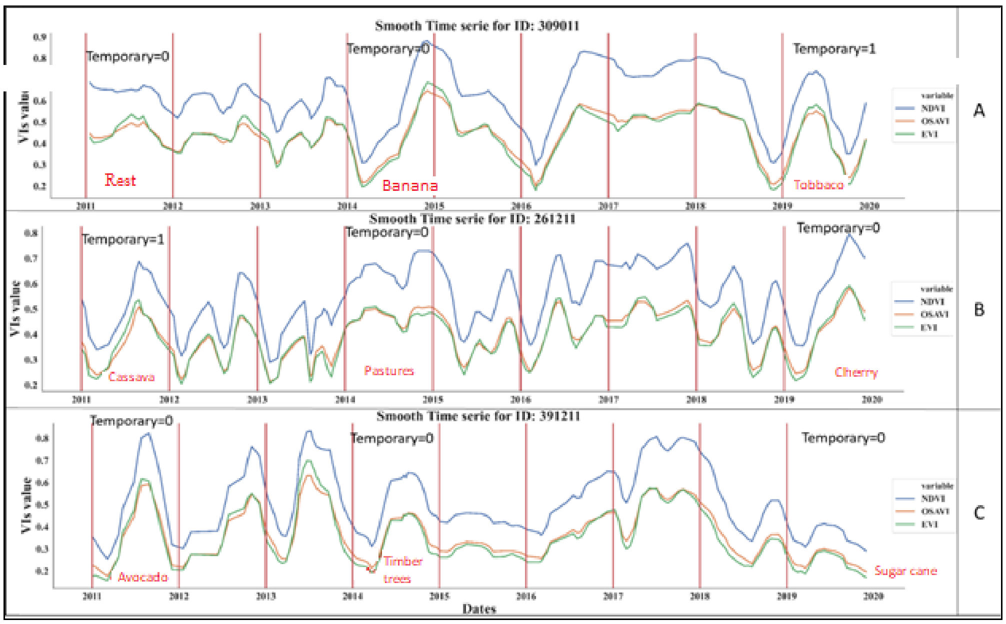
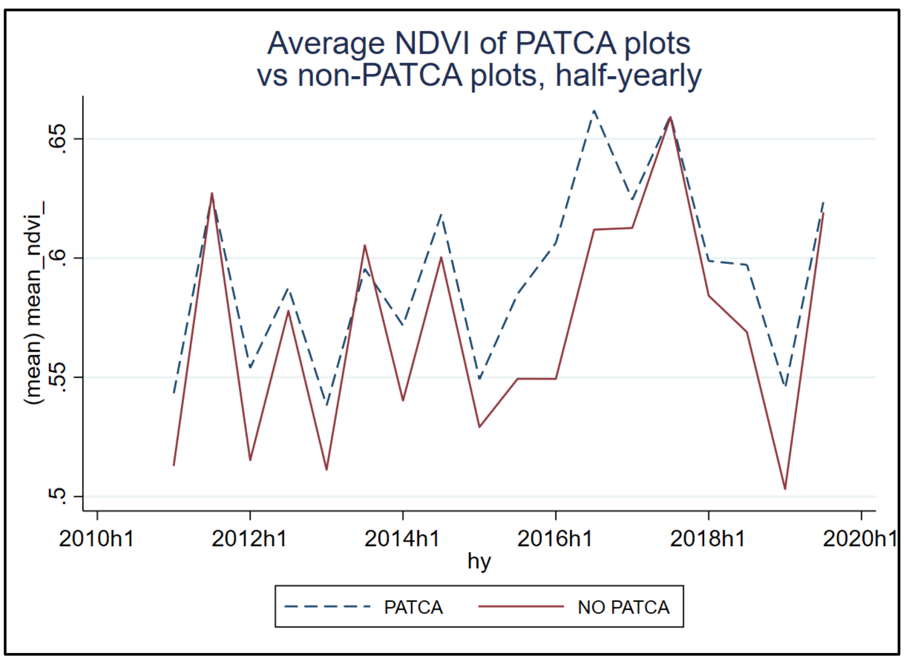


Figure 8B presents another example. In the self-reported survey, the producer reported to have a permanent crop in 2011. The figure suggests that this was switched to a temporary crop from 2012 to 2015, which was evidenced in the survey collected in 2014. The figure also indicates that since the end of 2016 until the end of 2017 values were stable. In 2018 the presence of a temporary crop is observed and finally in 2019 a permanent crop is confirmed by the second follow-up survey.

Lastly, Figure 8C shows the dynamics of a plot in the control group. The time series enables us to observe a trend from 2011 to 2014 with a permanent crop, since the vegetation indices values indicate an increasing phase, a peak, and a drop every year. On the other hand, NDVI values are stable from 2015 to the second semester of 2018, which suggest the presence of a permanent crop. Then, the plot starts the trend of a temporary crop until the end of 2019.

Using the monthly NDVI values, we graphed the average half-yearly NDVI values for both groups (control and treatment). Figure 9 shows evidence that, in general, the NDVI mean is higher for *PATCA* beneficiaries almost throughout the entire time series. This allows us to infer that program beneficiaries experienced a better plant health. The trends also show a decline of the NDVI for in the middle of each year included in the analysis, which portrays the regular agricultural cycle of the country where most of the harvests take place in the second semester.

Figure 9. Average NDVI for Beneficiary and Control Plots

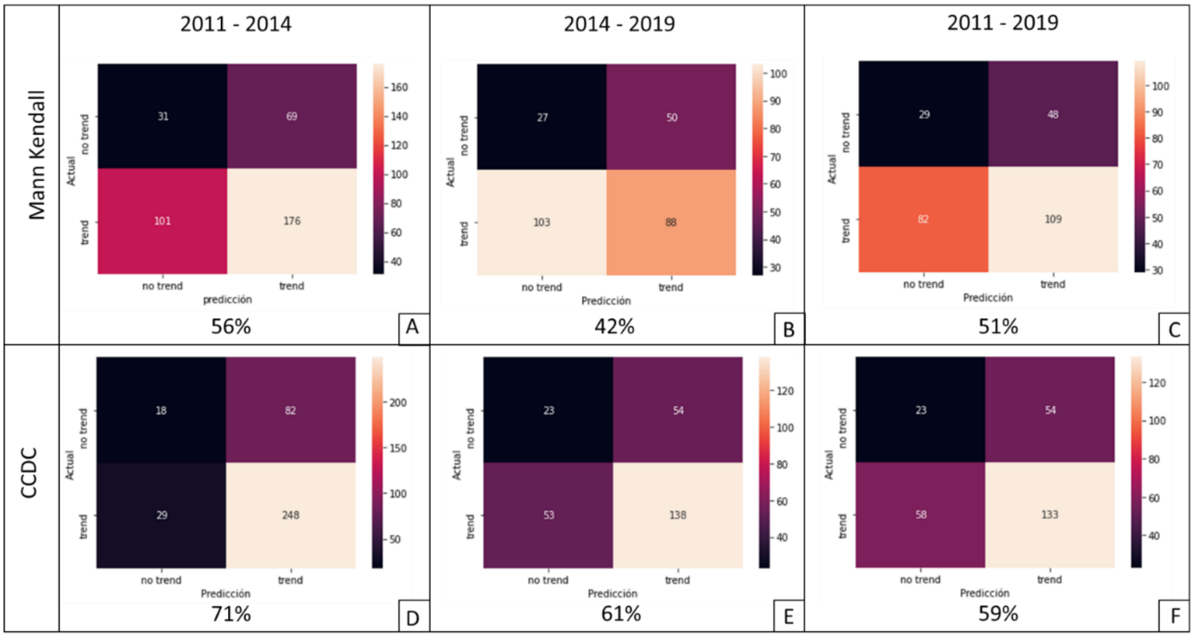


Validation of trend models and CCDC

Subsequently, trend models are applied to identify breaking points in the NDVI time series which would suggest a change in land use. For the validation of our models, we use data for the two rounds of follow-up surveys (2014 and 2019). The information of the plot geolocation was collected in the 2011 baseline survey and we have the same number of plots in the two follow-up rounds. However, during 2019 it was not possible to collect 73 surveys due to general attrition problems. For this reason, as some of variables needed for the validation of the models come solely from the surveys, 109 plots (73 farmers) were not included for validation. A total of 268 plots were included for the validation considering the periods of 2014-2019 and 2011-2019, while 377 plots were considered for the validation of the period of 2011-2014.

When comparing survey data with NDVIs for the period from 2011 to 2014, the results of the Mann Kendall and CCDC models provide a precision of 56% and 71%, respectively (Figure 10, panels A and D). For the period between 2014 and 2019, the Mann Kendal and the CCDC presented a precision of 42% and 61%, respectively (Figure 10, panels B and E). Finally, for the period between 2011 and 2019, the Mann Kendal had a precision of 51 % and CCDC a precision of 59% (Figure 10, panels C and F). This suggests that the CCDC model is a better fit for the data. However, both models have an appropriate precision.

Figure 10. Confusion matrix A - C) Mann Kendall, D - F) CCDC



Comparing with Zhu and Woodcock, (2014), the precision of the CCDC model is appropriate, especially for the period between 2011-2014 and 2014-2019. These details are improved because follow-up surveys do not offer information about the non-surveyed years (2012-2013, 2015-2018), so as the time frame of the analysis increases (2011-2019), the surveys can generate false negatives. In short, the model detects changes that are not recorded in the surveys due to the lack of information in the non-surveyed years, diminishing the precision of the model over time (Ángel, 2012).

For the period between 2011 and 2019, the Mann Kendal model indicates that 44% of the *PATCA* plots incurred in a land change compared to 38% of the control plots. The CCDC model indicates that 29% of the plots with *PATCA* made a change in land use compared to 37% of the control group (Table 5). However, these results are general averages descriptions and do not estimate a causal effect of the program. The following section presents the results of the causal effects using impact assessment methodologies based on counterfactual analysis.

Table 5. Land-Use Changes

Model			2011-2014	2014-2019	2011-2019
Kendal	Control	Land use changes	27%	46%	38%
	PATCA	Land use changes	48%	41%	44%
CCDC	Control	Land use changes	44%	39%	37%
	PATCA	Land use changes	16%	25%	29%

6.2 Results of the effect of the program on vegetation indices

As stated before, the analysis of trends and averages does not allow for the identification of the causal effect of the program on productivity or land use changes. Hence, to measure causal effects, we applied a Difference in Difference and an Event Study methodologies. First, we use a Difference-in-Difference model that compares the beneficiary group with the control group. This model provides a summary of the effects across all post-treatment years. The results of this methodology are presented in Table 6 (Equation 1). Overall, it is observed that the group of plots that received irrigation technology, present a higher vegetation index than the group of farmers who did not receive the treatment in the post treatment period. Specifically, this change corresponds to 0.0156 units for the NDVI index, which is equivalent to an increase of 2.7%, significant at 1%; and 0.0096 units, equivalent to a 2.4% increase for the OSAVI index, significant at 5%.

In addition, equation # 1 was also estimated using standard deviations of the annual vegetation indices as outcome variables. This was implemented to estimate disruptive changes in the indices that could provide signs of land use changes. In that sense, a stable NDVI over time would imply few changes in land use, while an NDVI with a high standard deviation would imply a larger change in land use. The results of columns (3) and (4) also show a higher standard deviation of the indices throughout the post-treatment period. This implies a higher variability of both indices during this period, since the indices degree of dispersion at the year and plot level is greater for the plots that received the treatment.

When the effects are disaggregated to understand the dynamic nature of treatment over time, estimating equation (2), three interesting results are found (Table 6). First, during the year when the technology is received *(Year 0),* the vegetation index for beneficiary plots is lower than the vegetation index for control plots, compared to one year prior to receiving the technology. The sign of the effect is preserved for any of the indices (NDVI or OSAVI), as well as the significance level of 1%. This implies that, receiving irrigation technology, alters farmers' behavior which is reflected in land use changes that cause a reduction of the NDVI. This might occur, for example, when farmers switch crops or renew plantations as lower productivity is observed during the planting period. This coincides with the results from the short-term analysis conducted with the baseline survey and the first follow-up (2011-2014) (Aramburu et al., 2019).

Second, the positive effects of the program are found, on average, three years after receiving the technology (Year + 3). Specifically, during the third year after receiving the technology, the vegetation index of the treated plots is significantly higher than the index of the control plots. This effect is significant at 5% and positive for both NDVI and OSAVI indices. This implies that technology effects on productivity are dynamic. Hence, it is possible that we are capturing a learning curve, which reaches its maximum peak three years after the technology is applied by the farmers. This is also in line with the previous short-term analysis where the authors suggest the presence of a learning-by-doing process, as estimations provide evidence that effects take time to materialize (Aramburu et al., 2019).

On the other hand, we did not find effects for the subsequent years. This might be because the elapsed time has been sufficient for the control group to adapt and acquire the technology, thus, reaching the productivity levels of the treatment group. This is validated with the field surveys collected for the 2019 agricultural cycle, which show that approximately 63% of the control farmers have adopted irrigation technology, indicating a catch-up effect by the control group.

Regarding the results on the standard deviation of the indices, we find that a greater dispersion of the indices is observed in the treated plots relative to the control plots, compared with the standard deviation of the index one year prior to receiving the technology. These results would suggest a land use change in the plots that received the treatment, since the degree of greenness of the crops varied more intensely than in non-treated plots.

Finally, as stated in Section 4, the Difference-in-Differences methodology requires to demonstrate that the assumption of parallel trends is binding. As observed in Table 3, the coefficients associated with seasonal events y = -3 and y = -2 are small and statistically insignificant. That is, two or three years before receiving the intervention, there were no significant differences in the average value of the NDVI, between treatment and control groups. This suggests that productivity might have behaved similarly in the pre-treatment period, and therefore the two groups can be compared.

In the Appendix, we present graphic illustrations of the estimated coefficients calculated in Table 6 for each period (Figure 11).

Table 6. Effects of *PATCA* on vegetation indices: Difference-in-Differences and Event Study.

Variables	(1) NDVI	(2) OSAVI	(3) SD NDVI	(4) SD OSAVI
Difference-in-Differences				
Patca x Post	0.0156***	0.0096***	0.0120***	0.00828***
	(0.0048)	(0.0035)	(0.0028)	(0.0021)
Observations	3,015	3,015	3,015	3,015
Plots	335	335	335	335
Event Study				
PATCA x Year-3	-0.00573	-0.00127	-0.00715	-0.00635
	(0.0122)	(0.00887)	(0.00819)	(0.00592)
PATCA x Year-2	-0.00365	-0.00235	-0.0106***	-0.00679**
	(0.00690)	(0.00536)	(0.00405)	(0.00320)
PATCA x Year0	-0.0295***	-0.0235***	0.00477	0.00260
	(0.00913)	(0.00698)	(0.00434)	(0.00334)
PATCA x Year+1	0.00947	0.00673	0.0164***	0.0110***
	(0.00884)	(0.00663)	(0.00475)	(0.00380)
PATCA x Year+2	0.00544	0.00302	0.0198***	0.0144***
	(0.00851)	(0.00669)	(0.00609)	(0.00497)
PATCA x Year+3	0.0214**	0.0167**	0.00676	0.00551
	(0.00983)	(0.00765)	(0.00485)	(0.00392)
PATCA x Year+4	-0.0126	-0.00879	0.0105**	0.00498
	(0.00800)	(0.00622)	(0.00488)	(0.00387)
PATCA x Year+5	0.00175	0.00142	0.0146**	0.00576
	(0.00848)	(0.00645)	(0.00573)	(0.00419)
PATCA x Year+6	-0.0113	-0.00967	0.0111*	0.00466
	(0.0109)	(0.00834)	(0.00637)	(0.00499)
PATCA x Year+7	-0.00866	-0.00188	0.0256***	0.0161***
	(0.00766)	(0.00578)	(0.00428)	(0.00335)
Observations	2,484	2,484	2,484	2,484
Plots	276	276	276	276

Notes: This table shows the estimated coefficients of the Event Study methodology shown in equation (2), as well as the estimated coefficients of the Difference-in-Difference model. Each column corresponds to the estimate of a different dependent variable. Columns (1) and (2) estimate the effects on the average of the indices and columns (3) and (4) the effects on the standard deviation. Omitted year: the year prior to receive the program (-1). Clustered standard errors at plot level. Includes plot and year fixed effects. * p <0.10 ** p <0.05 *** p <0.01.

6.2.1 Spillover effects

In addition of estimating the direct effects, the sample collected and the nature of the program implementation allowed us to identify the presence of spillover effects. For this, we compared control farmers located in beneficiary subzones (contaminated counterfactual) with pure control farmers.

Figure 12 shows that, on average, the contaminated counterfactual portrays a higher NDVI than the control group. Also, we estimated Equations #1 and #2 for both groups (Table 7). The results confirm the presence of some spillover effects. In fact, farmers who were located geographically closer to program beneficiaries have a greater NDVI than pure control producers, significant at 10%. This suggests that, by observing their neighbors, farmers could have been motivated to adopt irrigation. However, this effect is not corroborated when using the OSAVI index. Regarding index variability, the contaminated counterfactual also experiences greater variability for both indices, significant at 10% and 5%, respectively.

Figure. 12: Average NDVI of contaminated counterfactual and pure control plots

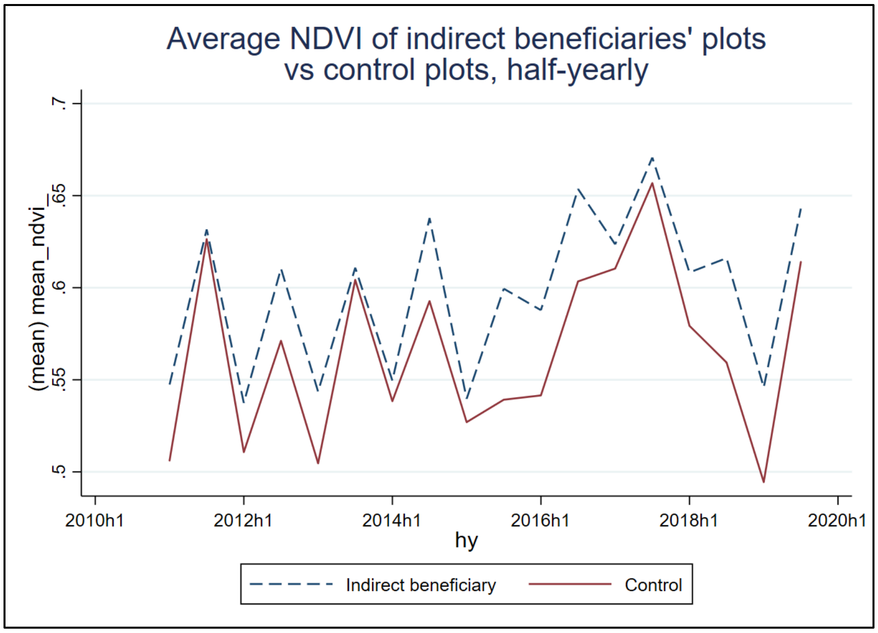


Table 7: Spillover effects

Variables	(1) NDVI	(2) OSAVI	(3) SD NDVI	(4) SD OSAVI
Difference-in-differences Model:				
Contaminatedx Post	0.0135*	0.00572	0.00774*	0.00690**
	(0.00712)	(0.00537)	(0.00462)	(0.00336)
Observations	2,232	2,232	2,232	2,232
Number of id	248	248	248	248
Covariates	No	No	No	No

Notes: This table shows the estimated coefficients of indirect beneficiaries and pure controls, using a Difference-in-Differences model. Each column corresponds to the estimate of a different dependent variable. Columns (1) and (2) estimate the effects on the average of the indices and columns (3) and (4) the effects on the standard deviation. Clustered standard errors at plot level. Includes plot and year fixed effects. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

7. Conclusions

This study combines data collected through surveys with remote sensing to analyze the causal effects of a technology adoption program implemented using a randomized control trial in the Dominican Republic. The PATCA program offered vouchers that partially financed the adoption of modern irrigation technologies to a group of randomly selected farmers to increase agricultural productivity. The vegetation indices, NDVI and OSAVI, were used as *proxy* variables of agricultural productivity, and were calculated through the spectral information provided by satellite images for a total of 377 plots, 129 beneficiaries and 248 control. These vegetation indices provide information on the nutritional status of the crops and in this specific case, the benefits from irrigation. In general, the relationship between NDVI values and plant health is directly proportional, which implies that a higher NDVI value is related to better plant health (Chuvieco, 1991).

To estimate the effects of the program on agricultural productivity, this study implemented impact assessment methodologies that allow the comparison of vegetative indices between the group of beneficiaries and the control group. By implementing a Difference-in-Differences methodology, we find that, in general, the beneficiary plots reported higher vegetation indices in the post-treatment period compared to the control group. This implies healthier crops, with greater vigor, and therefore, with a greater productivity than the control group.

Additionally, an Event Study model was implemented, which allows us to identify the effect of the program on productivity for different post-treatment periods. This methodology is especially useful to analyze the dynamics of the vegetation indices over time. The results show that the benefits from adopting irrigation technologies are obtained in the third year after the implementation of the technology. However, the coefficients of the subsequent periods are not significant, suggesting that the control farmers could have *catched-up* by adopting the technology. This has been validated with field surveys which suggest that farmers in the control group present a higher level of adoption of irrigation technologies in 2019. In addition, the program implementation using a two-stage randomized process allowed us to measure spillover effects at the geographical level. The results present some evidence of indirect impacts in neighboring farmers.

This study confirms the complementarity between data obtained through remote sensors (i.e. remote sensing) and field data. In general, remote sensing is a cost-effective technological alternative for the acquisition of data with greater temporality that facilitates the monitoring of crops through the creation of time series of vegetative indices, even for the years that field surveys were not collected. Therefore, this tool can be used to measure and monitor the effects of different policies and programs in the long term, thus complementing agricultural surveys.

This study also aims to encourage further research to contribute to the incipient literature that combines randomized experiments and satellite images to measure the impact evaluation of agricultural programs.

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Appendix

Figure 11. Estimated Coefficients