WORKING PAPER Nº IDB-WP-01741

Irrigation Infrastructure and Vineyard Productivity:

Evidence using Remote Sensing and Synthetic Difference-in-Differences in Argentina

Maja Schling
Magaly Saenz Somarriba
Carmine Paolo de Salvo
Rodrigo Chang

Inter-American Development Bank
Agriculture and Rural Development Division

August 2025

Irrigation Infrastructure and Vineyard Productivity:

Evidence using Remote Sensing and Synthetic Difference-in-Differences in Argentina

Maja Schling
Magaly Saenz Somarriba
Carmine Paolo de Salvo
Rodrigo Chang

Inter-American Development Bank
Agriculture and Rural Development Division

August 2025

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Gutierrez, Luis H.
Irrigation infrastructure and vineyard productivity: evidence using remote sensing and synthetic difference-in-differences in Argentina.
p. cm. — (IDB Working Paper Series ; 1741)
Includes bibliographical references.
1. Grape industry-Evaluation-Argentina. 2. Remote-sensing images-Argentina. 3. Irrigation farming-Evaluation-Argentina. 4. Irrigation-Equipment and supply-Evaluation-Argentina. I. Schling, Maja. II. Saenz Somarriba, Magaly. III. De Salvo, Carmine Paolo. IV. Chang, Rodrigo. V. Inter-American Development Bank. Agriculture and Rural Development Division. VI. Series.
IDB-WP-1741

JEL Codes: O13, O22, Q 12, Q15, Q18

Keywords: Irrigation, Productivity, Remote Sensing, Impact Evaluation, Argentina

http://www.iadb.org

Irrigation Infrastructure and Vineyard Productivity: Evidence using Remote Sensing and Synthetic Difference-in-Differences in Argentina

August 2025

Maja Schling[1], Magaly Saenz Somarriba[2], Carmine Paolo de Salvo[3], Rodrigo Chang[4]

Abstract:

This paper evaluates the long-term impact of rehabilitated irrigation canals under Argentina's PROSAP III program on vineyard productivity in San Juan province. We combine 20 years of Landsat-derived NDVI data with survey data from 299 grape producers and apply a synthetic difference-in-differences (SDID) framework to estimate causal effects. Additional robustness checks include propensity score matching and inverse probability weighting. Results indicate that canal rehabilitation increased NDVI by 0.9–1%, equivalent to yield gains of approximately 144 kilograms per hectare, with peak impacts of 2.5% (386 kg per ha) five years post-intervention. The study highlights the productivity benefits of irrigation investments and demonstrates the value of remote sensing for large-scale agricultural impact evaluations. Findings offer policy-relevant insights for designing and monitoring rural infrastructure programs in water-scarce regions.

Acknowledgments

We would like to thank the *Centro de Investigaciones en Estadística Aplicada* (CINEA) and the *Centro de Investigaciones Geográficas y Geotecnológicas* (CIGG) of *Universidad Nacional Tres de Febrero* (UNTREF) for their essential work in collecting and processing both the survey and remote sensing data. We are especially grateful to Walter Cortés for his expert support with the remote sensing analysis, and to Alejandro Galetto for his support in liaising with local actors during data collection efforts. Finally, we wish to acknowledge the team from the General Directorate of Sectoral and Special Programs and Projects (Dirección General de Programas y Proyectos Sectoriales y Específicos, DIPROSE) of the Secretariat of Agriculture, Livestock, and Fisheries (Secretaría de Agricultura, Ganadería y Pesca, MAGyP) for facilitating the data collection process and sharing valuable institutional and project-specific insights. We thank Cecilia Anderson for her careful translation of the manuscript into Spanish. Finally, we express our gratitude to the anonymous peer reviewers for their valuable comments, which helped improve the quality of this manuscript.

[1] Economics Senior Specialist – Agriculture and Rural Development, Interamerican Development Bank
[2] Consultant – International Finance Corporation
[3] Rural Development Senior Specialist – Agriculture and Rural Development, Interamerican Development Bank
[4] Consultant – Agriculture and Rural Development, Interamerican Development Bank

1. Introduction

Over the past three decades, agriculture in Latin America and the Caribbean (LAC) has grown at a rapid pace, transforming the region into one of the world's most significant contributors of food and agricultural commodities (FAO, 2021; Rosegrant et al., 2009). Although much attention is often directed toward major staple crops, many countries in the region also stand out for their high-value agricultural sectors, including horticulture, fruit production, and viticulture. In parts of Argentina, Chile, and Brazil, these specialized crops have become cornerstones for both export earnings and regional food security (Hall et al., 2011; Schling & Pazos, 2022). However, the region's agricultural landscape is marked by stark contrasts: while some producers operate at commercial scales with modern infrastructure, a substantial share of production is undertaken by small- and medium-scale farmers who face binding constraints related to water availability, technology adoption, and credit access (Cavatassi et al., 2011; Salazar et al., 2021). In addition, the inefficient and unsustainable use of agricultural inputs, and water in particular, continues to contribute to the overexploitation and contamination of the region's natural resources, threatening biodiversity and jeopardizing the sustainability of agricultural production. Rural infrastructure development is therefore an essential condition for boosting productivity, equity and sustainability in the region.

This duality is evident in Argentina, a country known for its robust agro-export sector but also home to a large population of family farmers struggling with low productivity in semi-arid environments (World Bank, 2007). The wine industry, particularly in provinces such as Mendoza and San Juan, underscores the pivotal role of irrigation in sustaining high-value crops in desert-like conditions (Fereres & Evans, 2006; Jara et al., 2017). Reliable water supply is essential to achieve both yield stability and quality parameters in grape production, yet many grape producers rely on canal systems, built decades ago that are now in need of rehabilitation or modernization. Addressing these infrastructure gaps holds significant potential for boosting productivity, stabilizing incomes, and strengthening the export competitiveness of Argentine viticulture.

In this context, evidence consistently shows that the provision of rural public goods in the form of rural infrastructure, such as irrigation, provides essential conditions for the development of markets and private production activities (see, for instance, Dercon et al., 2006; Fan, 2008; Jacoby, 2000; Jouanjean, 2013; Khandker et al., 2009). Investment in rural infrastructure has also been found to be both more effective and efficient than financing of private goods in boosting agricultural productivity, reducing rural poverty, and diminishing adverse effects in the management of natural resources (Fan et al, 2002; López & Galinato, 2007; Sills et al, 2015).

Recognizing the importance of modernizing irrigation for agricultural growth and poverty reduction, policymakers in Argentina and across LAC have introduced initiatives aimed at improving water distribution and management in smallholder contexts (Fan et al., 2008). Argentina in particular has a long history of implementing rural infrastructure projects through the Provincial Agricultural Services Program (PROSAP) with continued support from IDB since 1996. Until 2016, the Bank approved four investment loans at the request of the Argentinian government for a total of US$855 million to finance successive phases of the PROSAP program. The first three operations were completed in 2012, 2014 and 2017, respectively, and the fourth is still in execution, while a fifth operation with an investment amount of US$325 was approved in 2024.

Among other products, PROSAP financed the construction of more than 1,200 km of irrigation and drainage systems, over 1,000 km of rural roads, and more than 7,100 km of power lines for rural electrification. The third phase of the programmatic series, PROSAP III, specifically targeted canal rehabilitation in key agricultural provinces, including San Juan. Through partial grants and technical support, the program sought to upgrade irrigation canals, reduce seepage and water loss, and ensure that small and medium grape growers can reliably irrigate their vineyards (Saleth & Dinar, 2004). By strengthening farmers' capacity to manage water effectively, PROSAP III aimed to raise yields, and enhance the resilience of local production systems.

So far, however, robust impact evaluations of PROSAP's rural infrastructure investments have been limited, as most of the program's past evaluations employed descriptive or reflexive methodologies that did not allow causal inference of program impact. Given the financial scale of investments, and the continued implementation of rural infrastructure projects through the PROSAP program, more empirical evidence that is representative of the Argentinian context is needed. A general challenge has been that traditional farm surveys are costly to implement and can be prone to recall bias, underreporting, or measurement errors in yield data (Burke & Lobell, 2017). This measurement gap is especially critical for perennial crops such as grapes, where yield and quality vary considerably from season to season in response to water availability, climatic fluctuations, and vineyard management choices (Chaves et al., 2010).

Recent advances in remote sensing, however, present compelling opportunities to address these constraints. Satellite imagery, particularly through the Normalized Difference Vegetation Index (NDVI), allows researchers and policymakers to systematically track vegetative vigor over large geographic areas evaluate changes both in the long and short run (Sun et al., 2017). NDVI-based measures can detect subtle changes in canopy health that conventional surveys might overlook, offering an objective and high-frequency indicator of outcomes like productivity and water stress (Salazar et al., 2021). In addition to vegetation indices, remote sensing also facilitates the extraction of climatic variables, including temperature and precipitation, thereby enhancing the robustness of impact estimates by controlling for weather-related fluctuations. For regions such as San Juan, this approach provides a powerful tool for evaluating whether canal rehabilitations under PROSAP III effectively bolster vineyard productivity in the long run and enhance farmers' resilience to climatic variability.

This paper contributes to the literature by empirically estimating the impact of improved irrigation infrastructure on grape producers' outcomes in Argentina's San Juan region. Leveraging a combination of remote sensing data and survey-based information, we apply a synthetic difference-in-differences framework to rigorously assess how canal rehabilitation affects both short-term and longer-term changes in vineyard productivity (Arkhangelsky et al., 2021). By capturing high-resolution NDVI trends pre- and post-intervention, we aim to shed light on the dynamics of water availability in semi-arid viticulture, identifying when and how rehabilitated canals translate into measurable gains for local producers.

The results suggest that the rehabilitation of irrigation canals led to significant and sustained improvements in vineyard productivity. Using NDVI as an objective proxy, we estimate an average increase in vegetative vigor of 2.3–2.7% in treated plots relative to the control group, with peak gains of up to 5.7% observed five years after the intervention. These results are consistent with survey-based outcomes, which show production increases of up to 53%, expanded irrigated area, and a 20–28% reduction in the likelihood of yield losses attributed to irrigation problems. The findings are robust across alternative identification strategies, including propensity score matching, inverse probability weighting, and standard difference-in-differences, and are validated through placebo and falsification tests. Together, the evidence demonstrates that targeted investments in irrigation infrastructure can generate meaningful productivity gains in semi-arid viticultural systems, with implications for agricultural competitiveness, climate resilience, and rural development policy.

The remainder of the paper proceeds as follows. Section 2 reviews the empirical literature and presents the conceptual framework guiding the analysis. Section 3 provides background on the PROSAP III program and its implementation in San Juan. Section 4 describes the data sources used in the study, including both survey and remote sensing data. Section 5 outlines the empirical strategy, including the identification methods employed. Section 6 discusses the main results and robustness checks. The conclusions are found in section 7.

2. Literature Review and Conceptual Framework

Empirical literature has established a consistent link between the provision of rural infrastructure and productivity improvements, and that investments in public goods such as irrigation, roads, and access to energy sources tend to deliver higher rates of return than investments in private rural goods. For the case of rural roads, van de Walle & Cratty (2002) and Khandker et al (2008) use quasi-experimental methods to determine that improving rural transport infrastructure in Vietnam and Bangladesh, respectively, significantly lowers the time and cost of transportation, particularly among the poorest in the region. Other studies, such as by Escobal & Ponce (2002) in Peru, Lokshin & Yemtsov (2005) in Georgia, and Mu & van de Walle (2008) in Vietnam, estimate that improving rural roads has positive impacts on employment and salaries. Binswanger et al (1993) in a study in India, Levy (1996) in Morroco, and Khandker et al (2009) in Bangladesh also identify direct impacts on agricultural production, including the increased use of chemical fertilizers, the use of new technologies and inputs, as well as lowered costs of agricultural inputs. In the case of rural electrification, similarly rigorous econometric methods have been applied to highlight the positive impacts on household income (Khandker et al, 2009), employment (Dinkelman, 2011), and productivity (Lipscomb et al, 2013).

Irrigation plays a pivotal role in agricultural productivity, particularly in water-scarce regions. By providing reliable water supply, it enables crop cultivation in semi-arid and arid areas that would otherwise be unproductive (Rosegrant et al., 2009). Globally, irrigated lands account for only 16% of total cropland but produce roughly 36% of the world's harvest (FAO, 2021). These productivity differences arise because irrigation mitigates water stress and directly enhances plant growth and yields (Hussain & Hanjra, 2004).

A standard economic framework conceptualizes water as a critical input that shifts the production frontier outward by alleviating moisture constraints (Saleth & Dinar, 2004). Alternatively, within a production-function framework, irrigation can be treated as a form of "damage control," since rainfall deficits impose yield penalties that irrigation helps reduce (Lichtenberg & Zilberman, 1986). When farmers secure a stable water supply, they often invest in additional inputs such as fertilizers, improved seeds, and mechanized implements. Adeoti et al. (2007), for example, show that Ghanaian smallholders who adopted low-cost treadle pumps subsequently increased their usage of complementary inputs. Likewise, Aseyehegn et al. (2012) find that Ethiopian farmers with access to localized irrigation became more likely to use hybrid seeds and fertilizers, concluding that stable water availability reduced the risk of crop failure and made these investments more profitable. Duflo and Pande (2007) similarly observe that historically, canal-irrigated regions in India experienced higher adoption rates of modern farming practices than purely rainfed areas.

Irrigation's contribution to raising yields and farm profits has been well-documented in a range of contexts, including both developed and developing nations. In Spain, modernization of irrigation infrastructure in the Ebro Valley significantly improved productivity and water-use efficiency, with marked yield gains in maize and orchard crops (Berbel & Mateos, 2013). In Ghana, the adoption of treadle pumps enabled farmers to grow vegetables profitably in the dry season, contributing to higher household incomes (Adeoti et al., 2007). Dillon (2011) reports similarly strong profitability gains among small-scale irrigators in West Africa. Ecuador's *plataformas de concertación* approach, where farmer organizations jointly manage local irrigation, yielded robust productivity improvements by facilitating collective input procurement and equitable water allocation (Cavatassi et al., 2011).

Viticulture (grape production for wine) illustrates a specialized context in which irrigation can influence both yields and grape quality. In semi-arid areas, such as central Chile and western Argentina, irrigation is essential to establish and sustain productive vineyards (Fereres & Evans, 2006; Jara et al., 2017). In Argentina's Mendoza province, a long-standing network of irrigation canals, enables large-scale grape cultivation despite minimal rainfall (Agosta et al., 2012). Chile's irrigation systems have similarly underpinned the country's expansion as a significant wine exporter, though shortages of water and competition from other high-value crops create ongoing challenges (Hall et al., 2011).

Even though this empirical evidence supports the positive effect of rural infrastructure in general, and irrigation in particular, on agricultural production and productivity, there is a decided lack of rigorous studies of such projects in the Latin American context, and particularly in Argentina. Despite the fact that rural infrastructure projects have been publicly financed in Argentina through the PROSAP programmatic series for almost two decades, so far, most evaluations have relied on qualitative and quantitative methods that do not allow for causal inference. Only a handful of studies have examined interventions financed by PROSAP using quasi-experimental methods: Using a difference-in-difference methodology, Gibbons et al. (2016) evaluated the impact of an irrigation infrastructure project implemented in the second phase of PROSAP and found significant positive impacts on production (16%) and yields (14%). Two additional studies that evaluated PROSAP financed improvements to irrigation and drainage systems in 2013 and 2016 detected consistent positive productive impacts using difference-in-difference estimations (Rossi, 2013; Rossi, 2016).

The expansion of satellite-based remote sensing has considerably enhanced how irrigation impacts are measured. In the past, evaluations relied primarily on farm surveys, which can be time-intensive and prone to inaccuracies (Sun et al., 2017). Remote sensing provides spatially continuous, high-frequency indicators of vegetation health. Indices such as the Normalized Difference Vegetation Index (NDVI) capture discrepancies in red versus near-infrared reflectance, making them a strong proxy for crop vigor and biomass accumulation (Lillesand & Keifer, 2002).

Remote sensing time series, particularly NDVI, offer a powerful tool to evaluate the impacts of agricultural interventions on crop performance and vegetation dynamics For instance, Damania et al. (2019) document “greening trends” in the Sahel where irrigation investments extended vegetation cover into the dry season. In Latin America, Salazar et al. (2021) find higher NDVI-based productivity among Dominican farms that gained access to enhanced irrigation, suggesting remote sensing can reliably evaluate large-scale agricultural Similarly, Schling and Pazos (2022) use NDVI to track yield responses to a subsidy program in Argentina, showing remote sensing can capture gradual productivity gains over time. (Schling & Pazos 2022).

Taken together, these findings form a conceptual framework in which physical infrastructure, farmer decisions, and vineyard physiology interact to influence viticultural outcomes which can be captured by remote sensing data. Upgrades to canals or drip systems reduce seepage and improve water scheduling (Lichtenberg & Zilberman, 1986; Saleth & Dinar, 2004). With a more dependable water supply, farmers can adopt advanced methods, expand planted area, or invest in inputs like fertilizers or high-yield varieties (Cavatassi et al., 2011). These choices, in turn, affect vine growth: receiving sufficient moisture at crucial stages promotes higher yields and, under carefully managed deficit irrigation, better flavor and aromatic profiles (Chaves et al., 2010).

Remote sensing indicators, particularly NDVI, offer an objective way to track these changes in vine vigor and assess whether canal rehabilitation and new on-farm practices are indeed driving productivity gains (Sun et al., 2017). Over time, improved irrigation can bolster farmers’ resilience against weather extremes, although effective institutions are essential to prevent resource depletion or inequitable water allocation (Ward & Pulido-Velazquez, 2008). In this sense, irrigation is not simply an agricultural input but a socio-technical system, shaped by local governance, farmer engagement, and biophysical constraints. Viticulture exemplifies this dynamic, as crop yields, fruit quality, and environmental sustainability hinge on managing water with precision in arid climates (Hall et al., 2011).

3. PROSAP III

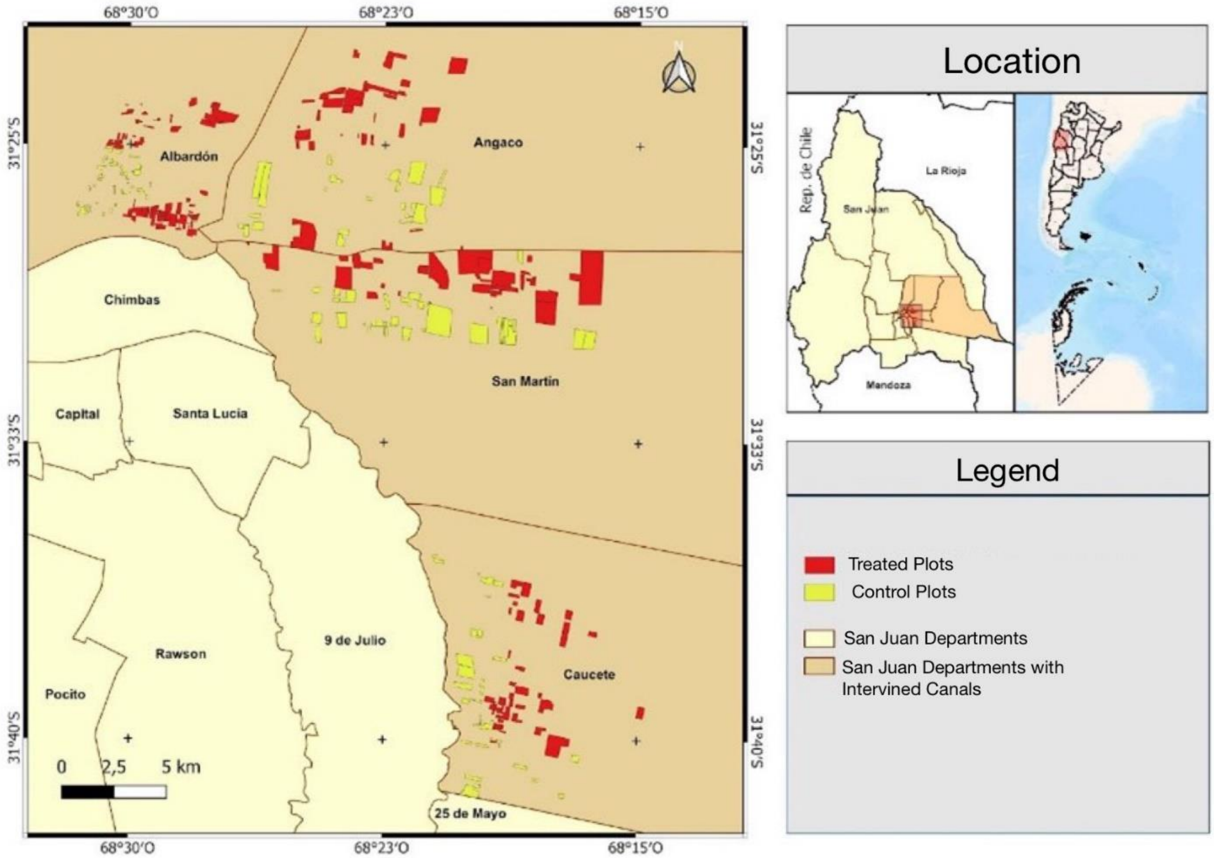
The agricultural sector in Argentina, particularly in its non-Pampean regions, faces substantial limitations due to deficiencies in rural infrastructure, which significantly constrains productivity and competitiveness. Although Argentina is globally recognized as a major agricultural exporter, with a strong comparative advantage in products from the highly productive Humid Pampas, regions outside this core area lag substantially behind. These regions, characterized by their arid or semi-arid climates[5], require reliable irrigation infrastructure to achieve sustainable agricultural production, particularly in high-value crops such as grapes.

Recognizing these constraints, the Provincial Agricultural Services Program has been the main policy instrument since 1996 to support rural development in Argentina. In its third phase,

[5] Figure A2 in the appendix shows cumulative precipitation of the area.

PROSAP III was implemented by the Argentine Ministry of Agriculture, Livestock, and Fisheries (MAGyP), and financed partially by the Inter-American Development Bank (IDB). The program, executed from 2011 to 2017, sought to enhance the competitiveness and productivity of regional agricultural economies through targeted infrastructure improvements and technical support. Among its key components, PROSAP III prioritized the rehabilitation and modernization of irrigation canals, particularly benefiting grape producers who are predominantly small- and medium-scale farmers in the regions of Mendoza and San Juan. Figure 1 below illustrates the area of intervention.

Figure 1: Area of Intervention



Source: UNTREF (2024)

The irrigation component of PROSAP III involved substantial infrastructure investments totaling approximately 32% of the program's resources. These interventions resulted in the rehabilitation and modernization of irrigation systems covering over 58,000 hectares, directly benefiting more than 5,000 agricultural producers. Specifically, the project upgraded canals to improve the efficiency of water conveyance, significantly reducing water loss and increasing the availability and reliability of irrigation water throughout the agricultural season. Additionally, investments included critical improvements in operational capacity, such as enhanced control systems and strengthened governance mechanisms within water-user associations, essential for sustainable system management.

Among the irrigation projects financed and implemented by PROSAP III was the project entitled "Agricultural Development and Management of the Irrigated Area of the North-25 de Mayo Canal" in San Juan Province in west-central Argentina. The project area was located in the Tulúm Valley, on the left bank of the San Juan River and included the Departments of Albardón, Angaco, San Martín, Caucete and 25 de Mayo. The project targeted 9 canal systems and included[6] waterproofing works, canal repair and adaptation of compartments and bridges covering 25,177 hectares with irrigation rights, 62% of which were under cultivation. The project aimed to increase water availability in canals through waterproofing, casing and canal repair, and improve the use of water resources at the plot level by reducing the evapotranspiration deficit. Further, the project provided distribution plans, maintenance of equipment and tools, new information and control systems. Additionally, the project implemented technical assistance to improve water management and application amongst farmers, by creating demonstration areas and demonstration pilot plots in 4 of the 9 treated canals that benefited more than 300 beneficiary farmers and their farm workers. These activities included guidance on how to incorporate new irrigation technologies at the farm level for different crop types, the use of pressurized irrigation systems, management of field drains, recovery of salinized soils, among other topics. These activities were supported by local agents of the country's public research and extension institute, the National Institute for Agricultural Technology (INTA), to ensure the use of the latest and most appropriate production practices. According to project documents, more than 1,200 farmers in the area benefited from these improvements, which were carried out in all canals simultaneously between December 2013 and November 2014.

The institutional arrangements governing canal rehabilitation and irrigation management in San Juan Province are characterized by a multilayered governance structure that attempts to balance state oversight with user participation. The San Juan Department of Hydraulics (DH), an autonomous public agency at province level, holds legal authority over both surface and groundwater management, including operation, maintenance, and planning of irrigation infrastructure. The Council, as DH's governing body, is composed of representatives elected by water users alongside technical appointees from the provincial government, to ensure user representation in key decisions such as budgeting, setting irrigation fees, and approving maintenance works. At the departmental level, decentralized Irrigation Boards (Juntas de Riego) are composed of elected irrigators in each department, while Canal Commissions (Comisiones de Regantes) operate in a similar manner for each canal or group of canals that serves more than 300 hectares. These bodies are responsible for operational planning, maintenance coordination, and conflict resolution at the local level. Each Irrigation Board plans and supervises irrigation and drainage operations for its department, while the Commissions handle day-to-day tasks such as monitoring water use and ensuring proper distribution. However, the project design document identified several weaknesses in institutional capacity within these organizations, including limited maintenance funding, weak enforcement of water schedules, and gaps in technical capacity and

[6] Specifically, the project financed the following infrastructure works: lining of 3,360 meters of earthen canals, casing of 12,580 meters of canals with precarious lining, reconstruction and repair of 6,850 meters of canal, replacement of 5 gates and their drive mechanisms, reconstruction of 1 bridge, cleaning of 10 hectares of surface area of the banks and accesses to the works, rehabilitation of 1,500 meters of service roads.

infrastructure monitoring (PROSAP-IICA, 2011). Thus, the project aimed to provide both the 5 beneficiary Irrigation Boards and 8 beneficiary Canal Commissions with capacity building activities to improve the technical and administrative management and ensure the sustainability of improved irrigation infrastructure.

4. Data Description

a. Sample Selection

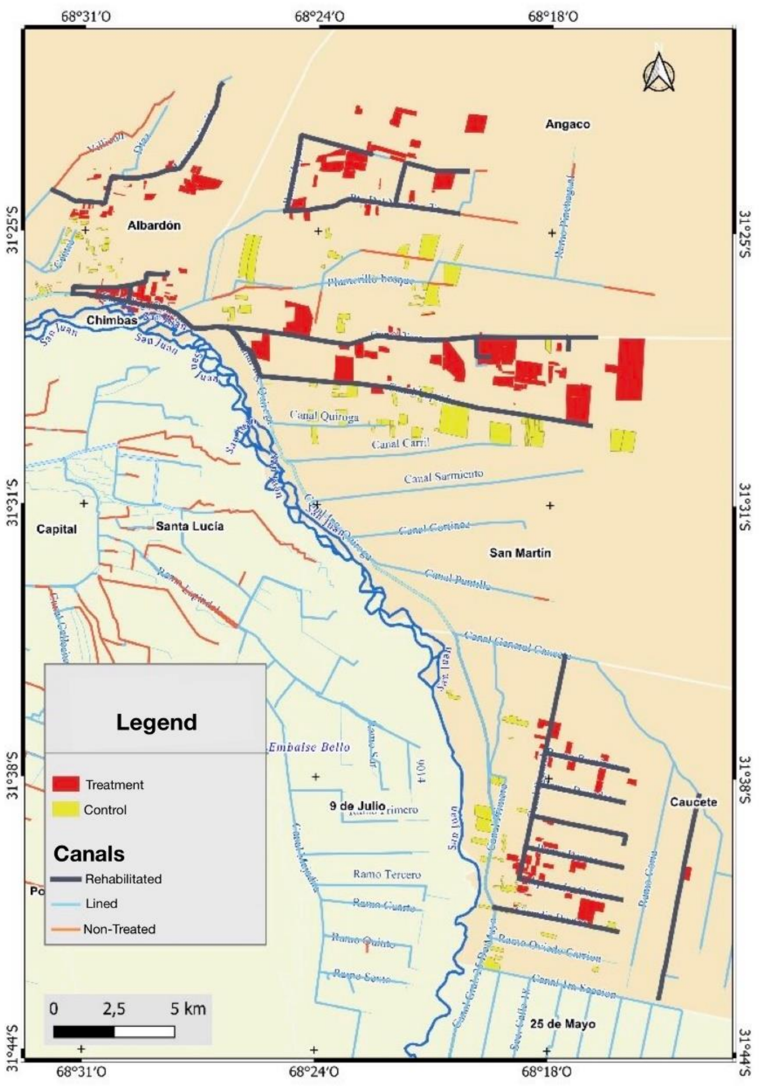
We utilize endline survey data collected as part of the ex post evaluation of the PROSAP III irrigation projects in four departments of San Juan Province. The survey, conducted in December 2023, was designed to capture the agricultural production and socioeconomic conditions of grape producers in the region during the 2022–2023 agricultural cycle. The questionnaire featured multiple modules, including, among others, farm geolocation, production inputs and practices, irrigation methods, and crop yields.

For the impact evaluation, four rehabilitated canals, each located in a different department, were selected, and a sample of their beneficiaries then constituted the treatment group. Specifically, the four treated canals selected for the evaluation were Canal Segundo in the department of Caucete, Canal Zapata in Angaco, Canal Tercero in San Martín, and Canal Centro-Norte and General Cañada in Albardón. These canals were prioritized for evaluation because they accounted for 70% of the total investment under the rehabilitation project, and where also sites of complementary technical assistance through the implementation of demonstration areas and pilots, thus allowing us to measure the effect of providing irrigation infrastructure and technical assistance as a package.

To construct a credible counterfactual, the control group was drawn from producers relying on four non-rehabilitated canals located in the same respective departments: Canal Primero (Caucete), Canal Plumerillo-Bosque (Angaco), Canal Laprida (San Martín), and Canal Campo Afuera (Albardón). The selection of these control canals was carried out in coordination with the provincial office and the Department of Hydraulics of San Juan, based on detailed field assessments. Control canals were chosen to ensure comparability in physical characteristics (degree of deterioration, hydric supply), agroecological conditions and farmer profiles. Matching treated and control sites within the same administrative department also helped minimize the risk of confounding due to unobserved regional shocks or concurrent interventions.

It is worth noting that the selection of canals for rehabilitation was primarily determined by financial and operational constraints rather than performance-based targeting. This reduces concerns about endogenous program placement and supports the credibility of the identification strategy. Figure 2 provides a spatial representation of the treated and control areas, as well as the irrigation infrastructure.

Figure 2: Spatial Representation of Treated and Control Units



Source: UNTREF (2024)

A systematic sampling procedure was implemented using the official list of irrigation user associations from the Irrigation Boards, and for each of the 8 preselected irrigation canals, 47 cases were drawn. This process initially resulted in a final sample comprising 245 cases for the treatment group and 157 cases for the control group, totaling 402 observations. However, in order to conduct a more homogeneous analysis that would be representative of the main target population of the project, we restrict the sample to such farmers who reported having produced grapes, thereby excluding 65 observations from the treatment group and 38 from the control group, which resulted in a final sample of 299 observations.[7] Table 1 presents the sample distribution by department.

[7] Other production included fruit, vegetables and olives, which implied significant differences in production systems and technology.

Table 1: Sample Distribution by Department

	Treatment	*Control*	*Total*
Albardón	52	27	79
Caucete	49	38	87
Angaco	36	17	53
San Martín	43	37	80
Total	180	119	299

It should be noted that this identification strategy implies that the estimator of interest will be the Average Treatment Effect on the Treated (ATET). Given the nature of the intervention, farmers located along treated canals could not be randomly assigned, and may indeed be located there due to underlying geographic, economic or agronomic factors that correlate with the outcome of interest. While this limits the possibility of extrapolating estimated effects to the general population, as would have been possible with the Average Treatment Effect (ATE) estimator, we maintain that the more policy-relevant estimator is ATET: public investment in productive infrastructure is usually targeted towards specific areas based on the same geographic, economic or agronomic factors that may motivate farmers to self-select to certain canals, and it is therefore of interest to understand what the impact is on the actual beneficiaries of such interventions, in order to inform continuation, improvement or scaling of the program. Therefore, we consider the ATET to be the more credible and policy-relevant estimator for this evaluation.

b. Survey Data

As seen in Table 2, the sociodemographic characteristics of respondents in both the treatment and control groups are broadly similar. The sample is predominantly male, with only 13% of respondents identifying as female in each group. The mean age is 57 years in the treatment group and 59 years in the control group. A slightly higher proportion of control-group respondents (68%) has completed at least a high school education, compared to 61% in the treatment group. In terms of residence, 44% of producers in the treatment group live on their farms, whereas 37% do so in the control group. Ownership patterns also differ: 84% of control-group respondents identify as owners, relative to 71% in the treatment group. Only a small fraction in either group are renters or managers, and approximately 22% in each group own additional farms.

As shown in Table 3, farmlands in the treatment group are larger than in the control group, as the average farm extension is 17.75 hectares in the treatment group compared to 12.33 hectares in the control group. In both groups, the vast majority of producers (over 85%) grow only grapes with very minimal use of mechanical harvesting. Producers in the control group hired more labor (3.14 workers) than the treatment group (2.53 workers). Notably, 37% of control-group producers report receiving technical assistance, whereas only 17% in the treatment group do so. Membership in a producer association is also more common in the control group (7%) than in the treatment group (1%).

Table 2: Sociodemographic Characteristics

	Treatment		Control	
	Mean	***SD***	***Mean***	***SD***
Female	0.13	0.33	0.13	0.33
Age	56.66	13.10	58.52	13.01
High school education	0.61	0.49	0.68	0.47
Resides in the farm	0.44	0.50	0.37	0.48
Owner	0.71	0.46	0.84	0.37
Renter	0.01	0.07	0.00	0.00
Manager	0.22	0.41	0.11	0.31
Owns additional farms	0.22	0.42	0.22	0.41
N	180		119	

Regarding the productive characteristics, both the harvested area and grape yields are somewhat larger in the treatment group. On average, treatment farms report 10.20 ha harvested in the previous cycle (vs. 6.34 ha in the control group) and 9.83 ha in the current cycle (vs. 5.98 ha). Yields average 16.97 t/ha in the treatment group, compared to 15.45 t/ha (in the control group).

Table 3: Farm and Productive Characteristics

	Treatment		Control	
	Mean	***SD***	***Mean***	***SD***
Total land extension (ha)	17.75	33.21	12.33	20.03
Grows grapes exclusively (%)	0.88	0.33	0.85	0.36
Has mechanical harvest (%)	0.04	0.19	0.03	0.18
N wage workers	2.53	2.34	3.14	2.28
Received technical assistance (%)	0.17	0.37	0.37	0.48
Has commercial agreements (%)	0.89	0.32	0.92	0.28
Is member of producer association (%)	0.01	0.11	0.07	0.25
Harvested extension last cycle (ha)	10.20	25.66	6.34	7.74
Harvested extension current cycle (ha)	9.83	24.93	5.98	6.90
Harvested grape extension (ha)	8.04	17.16	5.03	5.84
Total grape output (metric tons)	101.89	128.70	83.30	124.79
Yields (t/ha)	16.97	13.58	15.45	11.90
N	180		119	

Table 4 provides details on irrigation practices at the end of the project. The treatment group manages a larger mean irrigated area than the control group. Flood irrigation is the predominant system in both groups (63% in the treatment group and 52% in the control group), whereas border irrigation is more frequently employed in the control group (27% vs. 10%). Furrow irrigation is used at similar rates across both groups (26% vs. 23%). Drip irrigation is observed among 13% of treatment farms and 10% of control farms, while hose and siphon systems are rarely used by either group.

Table 4: Irrigation Characteristics

	Treatment		Control	
	Mean	***SD***	***Mean***	***SD***
Land extension under irrigation (ha)	15.46	29.48	8.75	15.32
Land extension under effective irrigation (ha)	9.19	24.24	5.34	7.60
Irrigation Systems:				
Flood irrigation	0.63	0.48	0.52	0.50
Border irrigation	0.10	0.30	0.27	0.45
Furrow irrigation	0.26	0.44	0.23	0.42
Hose irrigation	0.01	0.11	0.03	0.16
Siphon irrigation	0.01	0.07	0.00	0.00
Drip irrigation	0.13	0.34	0.10	0.30
N	180		119	

Table 5 summarizes self-reported production losses and their primary causes for both treatment and control groups. Overall, 54% of producers in the treatment group reported lower-than-expected production, compared to 31% in the control group. Irrigation issues emerged as the most frequently cited cause in both groups (76% and 80%, respectively).

Table 5: Production Losses

	Treatment		Control	
	Mean	***SD***	***Mean***	***SD***
Producer reports lower-than-expected production	0.54	0.50	0.31	0.46
Reported Reasons				
Rain issues	0.30	0.46	0.22	0.42
Irrigation issues	0.76	0.43	0.80	0.40
Sanitation issues	0.07	0.26	0.10	0.30
Hail	0.13	0.34	0.41	0.50
Cold weather	0.25	0.44	0.49	0.50
Scrub	0.02	0.15	0.01	0.11
Soil	0.01	0.11	0.02	0.16
Fertilizer issues	0.01	0.11	0.02	0.16
Other	0.12	0.33	0.05	0.22
N	180		119	

4.2 Remote sensing data

To monitor the temporal dynamics of crop conditions and growth in relation to the irrigation improvements, we employ a time series of remote sensing data from Landsat 7 and Landsat 8 imagery (2000–2023). Remote sensing data provide objective, consistent, and cost-effective measurements of agricultural productivity, overcoming limitations associated with traditional survey-based methods, such as potential inaccuracies, self-reporting biases, and the high costs and logistical complexities of extensive field surveys. Additionally, remote sensing enables high temporal frequency and broad spatial coverage, allowing for continuous monitoring and precise detection of changes in crop health. These monthly images were processed to extract a set of indices designed to capture changes in vegetation health, moisture content and overall productivity. Rigorous preprocessing steps, including geometric and atmospheric corrections as well as cloud masking, ensured that the imagery accurately represents the study area over time, facilitating the identification of seasonal patterns and long-term trends in crop performance.

To precisely identify the agricultural areas under analysis, high-resolution remote sensing data were integrated with detailed field-collected parcel boundaries. Field teams employed the “Field Area Measure” application on mobile devices to record the boundaries of each productive unit, generating .kmz files that captured the geometric outlines of the fields as declared by the producers. These files were imported into a GIS environment where extensive topological corrections refined the parcel boundaries to isolate only the cultivated portions. This process resulted in 213 georeferenced plots for the treatment group and 141 plots for the control group.

4.2.1 Normalized Difference Vegetation Index

We measure vineyard productivity through the Normalized Difference Vegetation Index (NDVI), a well-established proxy for agricultural output used to quantify vegetation density and health (Alface et al., 2019; Sun et al., 2017) which is derived from satellite imagery spanning 20 years. This extensive temporal coverage provides a unique advantage by allowing us to track long-term productivity trends, distinguish structural changes from short-term fluctuations, and establish a more reliable pre-intervention reference point. Additionally, NDVI offers high-frequency, objective observations that mitigate biases common in self-reported data (Adhikary et al., 2022) and allows for capturing spatial heterogeneity growth, thus enabling a more precise evaluation of targeted interventions (García-Pedrero et al., 2018).

Even though the use of NDVI could have some interpretability limitations, it is worth mentioning that NDVI has been used in viticulture, showing strong correlations with parameters that drive productivity. Studies have demonstrated that NDVI closely tracks vine growth dynamics; Sun et al. (2017) used Landsat imagery to establish a direct positive correlation between daily NDVI and final grape yield. This relationship extends to other characteristics; for example, Kasimati et al. (2021) demonstrated a strong positive correlation between NDVI and grape sugar. Notably, Lyu et al. (2023) identified a significant negative correlation between NDVI and sugar content, illustrating that excessive vigor can be detrimental to grape quality. Another study by Anastasiou et al. (2018) also found that satellite-derived NDVI at harvest correlated with other key attributes such as berry diameter. This literature confirms that NDVI is a reliable tool for monitoring vineyard productivity by capturing variations in both grape quantity and quality.

Additionally, we overcome any possible limitations of the use of remote sensing data by integrating NDVI with farm-level survey data on actual outputs. In this sense, we move beyond assumption to empirically relate satellite data to tangible economic outcomes in our context of vineyard productivity. We consider that this approach strengthens the causal interpretation of our findings and contributes to the literature seeking to combine remote sensing with ground tested data to reliably evaluate agricultural interventions.

Given this, the NDVI can be expressed as:

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

Where NIR (near-infrared) refers to the portion of the electromagnetic spectrum between approximately 0.7 and 1.1 micrometers, and RED refers to the visible red wavelengths, typically around 0.6 to 0.7 micrometers. Healthy vegetation reflects a large proportion of NIR light due to the internal structure of plant leaves while absorbing red light for photosynthesis. Consequently, higher NDVI values are typically associated with denser, healthier vegetation and greater yield potential (Kinyanjui, 2011; Lillesand & Keifer, 2002; Bégué et al., 2018; Chivasa et al., 2017). The suitability of NDVI as a proxy for crop yields has been demonstrated in several similar evaluation contexts, such as studies assessing agricultural interventions in Mexico (Ortiz-Monasterio & Lobell, 2007), South Africa (Bellora et al., 2017), the Dominican Republic (Salazar et al., 2021), and Argentina (Schling & Pazos, 2022).

NDVI was computed from a time series of satellite imagery using Landsat 7 Collection 2 Tier 1 (May 28, 1999–January 19, 2024) and Landsat 8 Collection 2 Tier 1 (March 18, 2013–November 16, 2024) via the Google Earth Engine platform. To ensure comparability between the two series, we applied a cross-calibration procedure to adjust for differences in sensor characteristics[8]. The satellite images were then aggregated to generate average monthly NDVI values for each plot, based on the georeferenced parcel boundaries and subsequent adjustments made to accurately delineate each agricultural area.

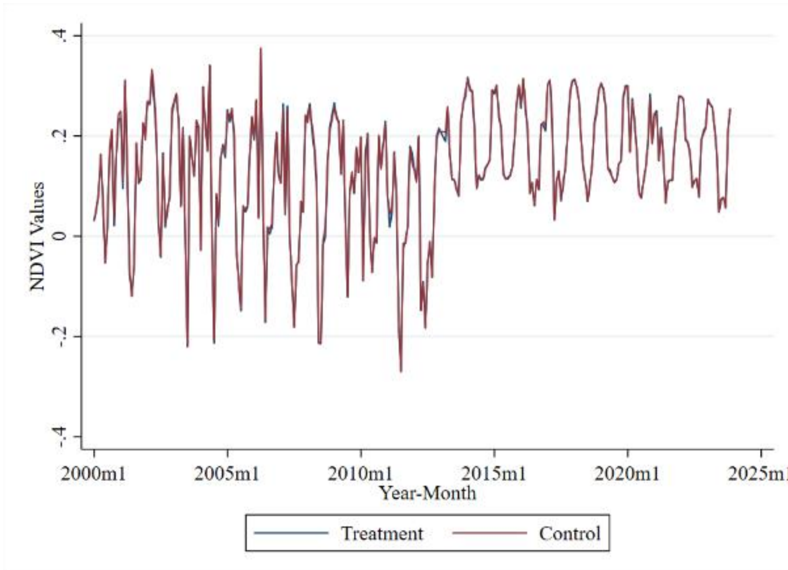
Given the inherent seasonality of the crop lifecycle, which is directly reflected in the NDVI values, we first applied a 12-month moving average to smooth out these seasonal fluctuations. This step helps to isolate the underlying long-term trend in vegetation health by removing the short-term variations driven by crop growth cycles (Becketti, 2013). Subsequently, we computed the agricultural year average of the smoothed series, where the agricultural year is defined from August to July (Ricce et al.,2013). This integrated approach captures both the long-term evolution of vegetation health and the distinct seasonal patterns of the crop, providing a robust framework for assessing the impact of irrigation improvements.

Figure 3 displays the monthly series of NDVI data for both the treatment and control group. Panel A presents the raw NDVI series, which exhibits pronounced seasonal fluctuations. Panel B shows the same NDVI time series after applying a 12-month moving average to smooth out short-term seasonal variations. This process highlights the broader trends in vegetation health over time. While the seasonal "noise" is reduced, differences between the treatment and control groups remain observable in certain periods.

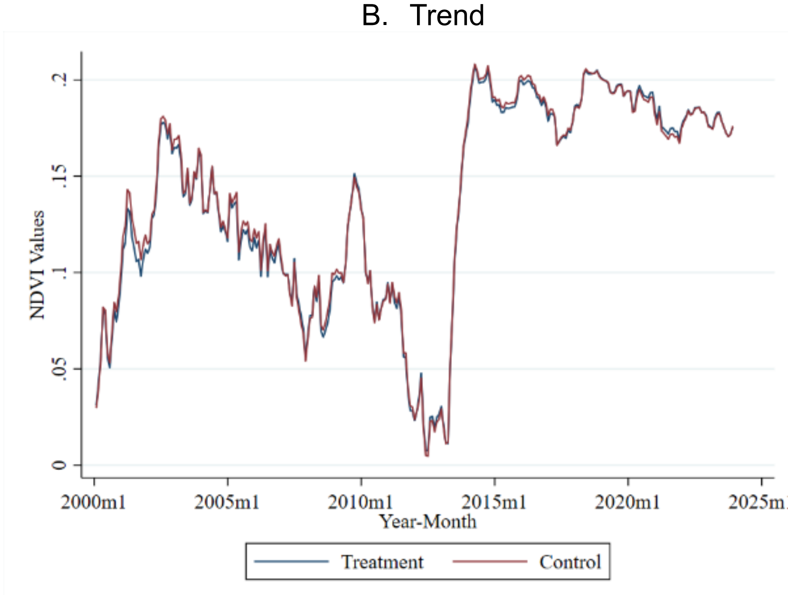
[8] To ensure consistency across sensors, NDVI values from Landsat 7 and 8 were normalized using radiometric calibration, spatial alignment, and scale adjustment techniques to account for differences in sensor resolution and performance, following best practices in multi-sensor vegetation monitoring described in Ezimand (2021).

Figure 3: NDVI Series

A. Raw Data



B. Trend

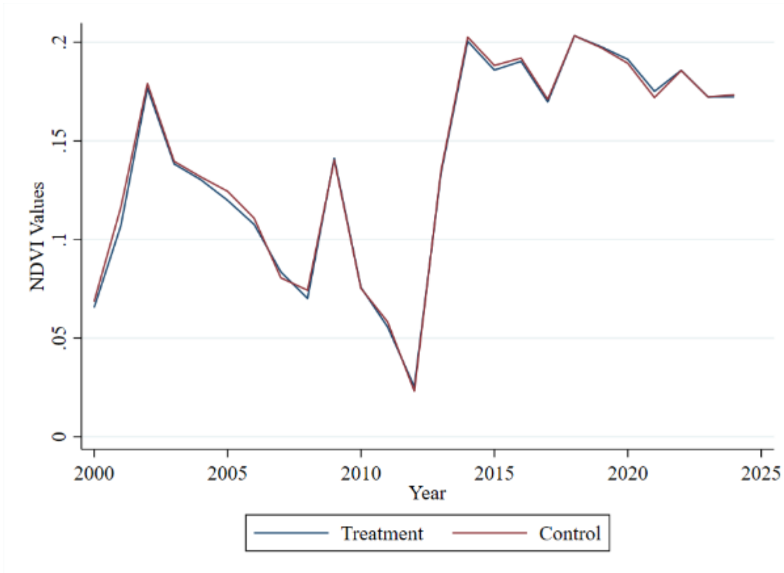


Notes: Smoothing of the series is done with the *tssmooth* command in Stata.

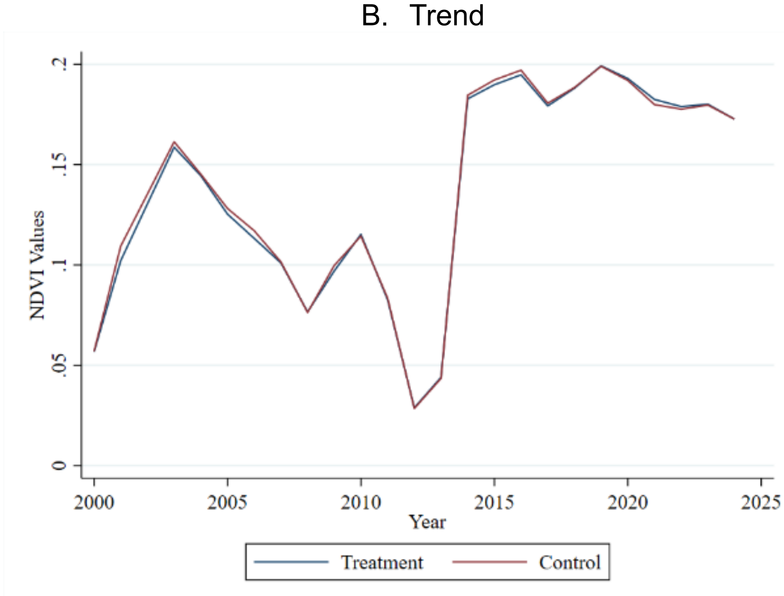
Figure 4 presents the agricultural year average NDVI values for both the treatment and control groups. By averaging the NDVI data over the agricultural cycle, the figure captures underlying shifts in vegetation vigor while still reflecting the crop's inherent seasonality. The observed patterns likely reflect both climatic conditions and changes in vineyard management practices over time. Notably, both the raw and smoothed annual trends indicate similar patterns for the two groups across the 23-year period.

Figure 4: NDVI Series Aggregated by Agricultural Year

A. Raw Data



B. Trend

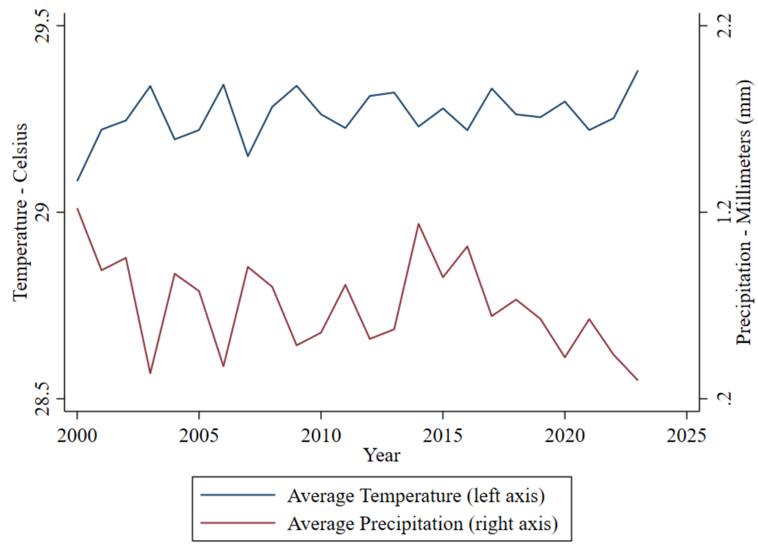


Notes: The period of the agricultural year is August through July as per Ricce et al. (2013).

In addition to the NDVI, our analysis incorporates climatic variables, specifically temperature and precipitation data, to account for weather variability that may affect crop productivity independently of irrigation improvements. Monthly temperature and precipitation records were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF), covering the same study period (2000–2023). These climate data underwent quality checks and were aggregated at the plot level, ensuring accurate representation of local climatic conditions for each georeferenced parcel.

Figure 5 presents the long-term trends in these climatic variables from 2000 to 2023. Average temperature (°C), represented by the blue line and plotted on the left y-axis, has gradually increased over time, suggesting a warming trend in the region. Meanwhile, average precipitation (mm), shown by the red line on the right y-axis, has steadily declined, with noticeable fluctuations from year to year. These shifts in climate conditions are important to consider, as they can impact crop performance independently of irrigations improvements (Lobell & Field, 2007).

Figure 5: Temperature and Precipitation Trends



Source: European Centre for Medium-Range Weather Forecasts (ECMWF)

5. Empirical Strategy

This study evaluates the causal effects of rehabilitated irrigation systems, implemented under the PROSAP program, on vineyard production in Argentina's San Juan Province. A key challenge in establishing the causal impact of programs such as PROSAP lies in selecting an appropriate control group, that allows for the causal attribution of estimated impact. Ideally, the control group should share similar characteristics with the treatment group in terms of geographic, climatic, and socioeconomic factors to ensure a valid comparison. In this study, the control group was selected based on hydrological similarity to the treated canals, as well as its location within the same administrative departments, reducing the risk of systematic differences that could bias the impact estimates. A major limitation of our data is that self-reported data, including both outcome variables and relevant covariates are only available for the endline survey, preventing the use of a difference-in-differences approach. Given the absence of baseline data and the observed differences in certain characteristics between groups, we employ a propensity score matching (PSM) approach to improve the comparability and mitigate potential selection bias. For example, the two groups differ in access to technical assistance and participation in producer associations, suggesting that the control group may have had better access to support services and social networks that could have influenced production outcomes independently of the intervention. These differences highlight the need to match for observable characteristics to more accurately estimate the impact of the project. Specifically, we estimate the probability of being in the treatment group based on observable covariates such as producer characteristics and farm attributes. We then use this propensity score to match treatment producers to similar control producers, yielding a matched subsample with more balanced observable characteristics.

In addition to PSM, we implement inverse probability weighting (IPW) to address self-selection bias and exploit the full sample. IPW reweights each observation by the inverse of its estimated propensity score. For each observation iii, the weight is defined as:

$$\omega_i = \frac{Treatment_i}{p(Treatment_i)} + \frac{1 - Treatment_i}{1 - p(Treatment_i)}$$

This approach assigns greater weight to treated observations with lower propensity scores and control observations with higher scores, thereby constructing a counterfactual that uses all available data. The parametric nature of IPW further allows for the estimation of standard errors within a regression framework, an advantage highlighted in the literature (Rosenbaum, 1987; Hirano and Imbens, 2001; Cavatassi et al., 2011).

By employing both PSM and IPW, we ensure a robust assessment of treatment effects. While PSM improves comparability by explicitly selecting a matched subsample with similar observable characteristics, it reduces sample size and may introduce inefficiencies. Conversely, IPW leverages the entire dataset by reweighting observations, providing greater statistical power and enabling regression-based inference. Combining these methods enables us to check the robustness of our results and assess the consistency of our findings across different approaches to addressing selection bias.

Despite the benefits of matching, another limitation of this study is the nonrandom selection of canals, which can introduce endogeneity. Because the selected canals and their surrounding areas may differ systematically from those that were not rehabilitated, estimates of the program's effect risk being biased. To address these concerns and to leverage the availability of remote sensing data, novel high-frequency data spanning a long time horizon, we employ the Synthetic Difference-in-Differences (SDID) design developed by Arkhangelsky et al. (2021). This approach, distinct from other recent methodologies designed for staggered adoption of treatment contexts, such as Callaway & Sant'Anna (2021) or Chaisemartin & D'Haultfoeuille (2020), allows us to further mitigate baseline imbalances while capitalizing on innovative data to generate a robust estimate of the program's impact.

SDID relaxes the strict parallel trends assumption inherent in traditional Difference-in-Differences (DiD) methods and combines key features of both DiD and the synthetic control approach. Specifically, it optimally weights the control units and pretreatment periods to produce a credible counterfactual for the treated units. In this sense, the methodology lends itself to making the assumption of parallel trends less restrictive, assuming that it is maintained only after adjusting for differences in the pre-treatment trend using weights. This approach reduces bias when baseline characteristics differ between treatment and control groups and thereby improves the validity of our causal estimates.

Mathematically, the average treatment effect on the treated $\hat{\tau}$ is obtained by minimizing the squared distance between the observed outcomes of the treatment group and a weighted combination of control units over time:

$$\hat{\tau} = argmin_{\tau,\mu,\alpha,\beta}\{\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau)^2\widehat{\omega_i}\widehat{\nu_t}\}$$

where $\widehat{\omega_i}$ (unit weights) and $\widehat{\nu_t}$ (time weights) are constrained to be nonnegative and sum to one. These weights align the pretreatment characteristics of the treated units with those of the control units, ensuring that post-treatment differences in outcomes can be attributed more confidently to the intervention itself (Clarke et al., 2023). Further details on the weighting procedure can be found in Arkhangelsky et al. (2021).

The analysis uses a balanced panel of *N* producers observed over *T* years, from 2001 to 2023. We obtain NDVI data monthly from satellite imagery and aggregate it to annual means to match the agricultural calendar. We also include annual precipitation and temperature data to account for weather-related variations in vineyard productivity. We define the treatment period as 2016 to 2023, since 2016 is the first agricultural year in which the rehabilitated canals were fully operational. The binary treatment variable D_{it} takes the value of 1 if producer i in year t is treated. Standard errors are clustered at the canal level to account for shared shocks among producers who rely on the same canal.

In the SDID framework, our model can be represented as:

$$Y_{it} = \mu + \alpha_i + \beta_t + D_{it}\hat{\tau} + \varepsilon_{it}$$

Where:

Y_{it}	is the outcome of interest (e.g., mean NDVI),
α_i	are producer fixed effects (capturing time-invariant differences across producers),
β_t	are year fixed effects (accounting for common shocks that affect all producers in a given agricultural year),
D_{it}	is the treatment indicator, and
ε_{it}	is the error term.

The SDID algorithm then optimally chooses unit and time weights such that the weighted average outcome for the control units in the pretreatment period matches as closely as possible those of the treated units.

5.1 Robustness and Validity Checks

Although SDID relaxes the strict parallel trends assumption, required by traditional Difference-in-Differences (DiD), by replacing it with the assumption of parallel trends conditional on weighting, it still requires that no unobserved confounders differentially affect the treatment group post-intervention. To assess the validity of our identification strategy, and the robustness of our findings, we implement a series of complementary tests, each rooted in best practices from the causal inference literature.

First, we perform a placebo test by applying SDID to the pretreatment periods only, assigning a false treatment date prior to the actual intervention. This test, common in DiD application (Bertrand et al., 2004; Abadie et al., 2010), ensures that our methodology does not detect a false effect in the absence of a real intervention.

Second, we carry out a falsification test by examining outcomes that should remain unaffected by canal rehabilitation. This test helps detect whether unobserved confounding might be biasing our results (Rosenbaum, 2002).

Third, we test the robustness of our estimates to alternative measures of NDVI, comparing results derived from mean NDVI with those using maximum NDVI. Maximum NDVI captures the peak vegetative vigor during the growing season and is often used in agricultural remote sensing as a proxy for optimal crop performance (Lobell et al., 2015; Lykhovyd et al., 2022). Consistent results across both indicators strengthen confidence that the estimated effects are not driven by how we define outcome measurement.

Lastly, we replicate the analysis using a more traditional event-study DiD design[9] to assess the reliability of our estimates relative to SDID's weighting procedure and whether our findings are model dependent (Clarke et al., 2023)

It is also worth noting the potential concern of spatial spillovers of treatment, a topic that has been addressed in recent literature (for instance, see: Deininger & Xia, 2016; Marbler, 2024; Aramburu et al.,2019). That is, the treatment of one unit may influence nearby untreated units through shared resources, informal knowledge transfer, or market effects. In our context, such spillovers could arise if rehabilitated canals indirectly benefited neighboring producers through improved water availability, informal knowledge of improved irrigation practices, or coordination within irrigation networks. However, several features of the identification strategy mitigate this concern. Treated and control canals were deliberately selected in different hydraulic systems and physically separate zones within the same departments, reducing the likelihood of spillovers. Also, water governance structures in San Juan are organized by canal-specific irrigation commissions, which limit cross-canal coordination. Nonetheless, we acknowledge this as a possible source of attenuation bias and encourage future work to further explore spatial dynamics using more granular geospatial methods.

6. Results

This section presents the empirical findings from our analysis, combining survey-based production with remote sensing outcomes.

6.1 Survey based outcomes

Our propensity score matching (PSM) approach employs 1-to-1 nearest neighbor matching with replacement while adhering to the common support condition. The matching algorithm uses respondent characteristics that are considered exogenous to program participation, including age, gender, education, membership in producers' organizations, and farm ownership, along with productive factors such as the use of mechanical harvest machinery. This procedure produced a

[9] See appendix A5 for a description of the event study difference-in-differences methodology.

matched sample of 251 producers, consisting of 178 treated and 73 control group producers. Table 6 presents the balance test between the treatment and control groups on the matched sample; although some differences persist, the groups are largely comparable in terms of observed characteristics.

Table 6: Balance Test

	Treated		Control			
	Mean	SD	Mean	SD	Difference	
Female^	0.13	0.34	0.12	0.33	0.01	
Age^	56.66	13.10	58.32	13.68	-1.65	
High School Education^	0.61	0.49	0.63	0.49	-0.02	
Resides in the farm^	0.44	0.50	0.40	0.49	0.05	
Owner^	0.71	0.46	0.82	0.39	-0.11	*
Renter	0.01	0.07	0.00	0.00	0.01	
Manager^	0.22	0.41	0.12	0.33	0.10	*
Owns additional farms^	0.22	0.42	0.21	0.41	0.02	
Total land extension (ha)	17.90	33.36	12.08	19.15	5.82	
Harvested extension last cycle (ha)	10.28	25.79	6.10	7.50	4.18	
Harvested extension current cycle (ha)	9.91	25.06	6.08	7.50	3.83	
Grows grapes exclusively	0.88	0.33	0.84	0.37	0.04	
Has mechanical harvest^	0.04	0.19	0.03	0.16	0.01	
Land extension under irrigation (ha)	15.58	29.62	8.23	12.99	7.35	**
Land extension under effective irrigation (ha)	9.26	24.37	5.23	7.95	4.03	
Received technical assistance	0.17	0.38	0.33	0.47	-0.16	***
Has commercial agreements	0.89	0.32	0.95	0.23	-0.06	
Is member of a producer association	0.01	0.11	0.01	0.12	0.00	
N wage workers	2.54	2.35	3.23	2.46	-0.69	**
Harvested grape extension (ha)	1.35	1.16	1.08	1.02	0.27	*
Log Total grape output (t)	3.79	1.56	3.38	1.62	0.40	*
Log Yields (t/ha)	2.43	1.05	2.30	1.20	0.13	
N	178		73			

Notes: Variables marked with ^ were used in the PSM procedure.

Table 7 presents the estimated treatment effects of enhanced irrigation canals on four outcomes: logged production volume (Panel A), land extension under irrigation rights (Panel B), land extension effectively under irrigation (Panel C), and the likelihood of yield losses attributable to irrigation issues[10] (Panel D). The estimates are provided for three different sample specifications:

[10] This is a binary variable that takes the value 1 if the producer reported experiencing yield losses and identified irrigation issues as the primary cause.

the full sample (Columns 1 and 2), the matched sample (Columns 3 and 4), and the inverse propensity weighting (IPW) estimates (Columns 5 and 6).

Table 7: Effects Of Enhanced Irrigation Canals On Grape Production

	Panel A: Log Grape Output (kg)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.314*	0.432**	0.402*	0.532***	0.268	0.384**
	(0.185)	(0.173)	(0.219)	(0.204)	(0.182)	(0.168)
N	299	299	251	251	297	297
	Panel B: Land Extension Under Irrigation Rights					
Treated	0.293**	0.429***	0.338**	0.498***	0.216**	0.362***
	(0.118)	(0.095)	(0.143)	(0.113)	(0.106)	(0.089)
N	299	299	251	251	297	297
	Panel C: Land Extension Effectively Under Irrigation					
Treated	0.235**	0.359***	0.266**	0.409***	0.161*	0.292***
	(0.101)	(0.085)	(0.121)	(0.101)	(0.093)	(0.083)
N	299	299	251	251	297	297
	Panel D: Reason for yield losses: Irrigation					
Treated	-0.205***	-0.212***	-0.276***	-0.280***	-0.206***	-0.199***
	(0.057)	(0.058)	(0.067)	(0.067)	(0.058)	(0.057)
N	299	299	251	251	297	297
Matching Sample	No	No	Yes	Yes	No	No
IPW	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes:

- Standard errors in parenthesis
- Covariates used in PSM and IPW: Female, age, high school education, resides in EA, owner of EA, manager of EA, owns additional farms, mechanical harvest, and producer organizations
- IPW average treatment effects estimated using the command *teffects* in Stata
- Additional controls include department fixed effect, number of hired workers and harvesting grapes exclusively.

The findings indicate that enhancements to irrigation canals are associated with significant improvements in production, with treated producers exhibiting a 31.4% to 53.2% increase in output relative to the control group. This production boost appears to be driven by increases in both the area of land under irrigation rights and the area effectively irrigated; treated producers experienced statistically significant gains in effectively irrigated land ranging from 16.1% to 40.9% across the models. Moreover, the enhanced irrigation infrastructure is associated with a significant reduction in the likelihood of reported yield losses attributed to irrigation problems. Specifically, the likelihood that a producer identifies irrigation issues as the main cause of yield loss decreases by an estimated 20.5% to 28.0%. The magnitude and direction of estimated coefficients remain relatively stable across different specifications, confirming the robustness of results.

6.2 Remote sensing outcomes

As a core component of our analysis, we rely on the Normalized Difference Vegetation Index (NDVI) as an objective measure of changes in crop yield. NDVI data, derived from Landsat imagery and aggregated to match the agricultural year, capture both seasonal dynamics and long-term trends in vineyard productivity. To validate this proxy, we confirm a strong positive correlation between NDVI and self-reported crop yield: a one-percent increase in NDVI is associated with a **1.30% to 1.54% increase** in yield, consistent with the expected relationship in viticulture.[11]

We estimate the treatment effect on NDVI using the Synthetic Difference-in-Differences (SDID) approach, which constructs a weighted counterfactual that closely replicates the pre-intervention trends of the treatment group. Figure 6 displays the evolution of NDVI for treated and control plots relative to the completion of the canal rehabilitation (the 2015–2016 agricultural cycle is indicated by the vertical line at period 0). Prior to the intervention, the two groups followed parallel trends, with no statistically significant differences observed in the pre-treatment period.

In the post-treatment period, the results indicate a clear positive trend, with an average increase in NDVI of 0.002 for the treated plots. Relative to the preintervention average NDVI of the control group (0.114), this represents a 1.75% increase. The effect is statistically significant in both the raw and smoothed (trend) series. Given the established relationship between NDVI and yield in our data, this change corresponds to an estimated 0.93% to 1.00% increase in crop yields. In absolute terms, based on an average yield of 15.45 metric tons per hectare in the control group, this translates to an additional 144 kilograms per hectare. Notably, the difference in NDVI peaks at 0.005 units in the fifth year after the intervention, equivalent to a 2.5% increase relative to baseline NDVI, and corresponds to an estimated 386 kilograms per hectare of additional yield. These findings suggest that the improved irrigation infrastructure had a sustained and meaningful impact on vineyard productivity over time.

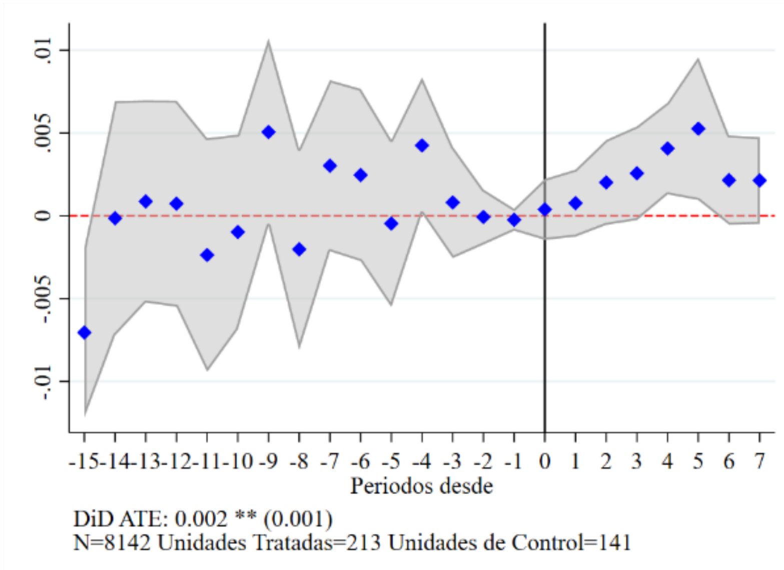
6.3 Robustness Checks

To assess the reliability of our findings, we conducted several robustness and sensitivity tests. First, we examine the pre-treatment trends by conducting a placebo test. We artificially assign 2009 as the year in which the rehabilitated canals were operational, even though the actual intervention occurred later. Figure 7 displays these results. In the raw series, some statistical differences appear; however, these differences do not persist in the smoothed series. This suggests that the observed variations are short-term fluctuations rather than shifts in long-term trends, reinforcing the validity of our results.

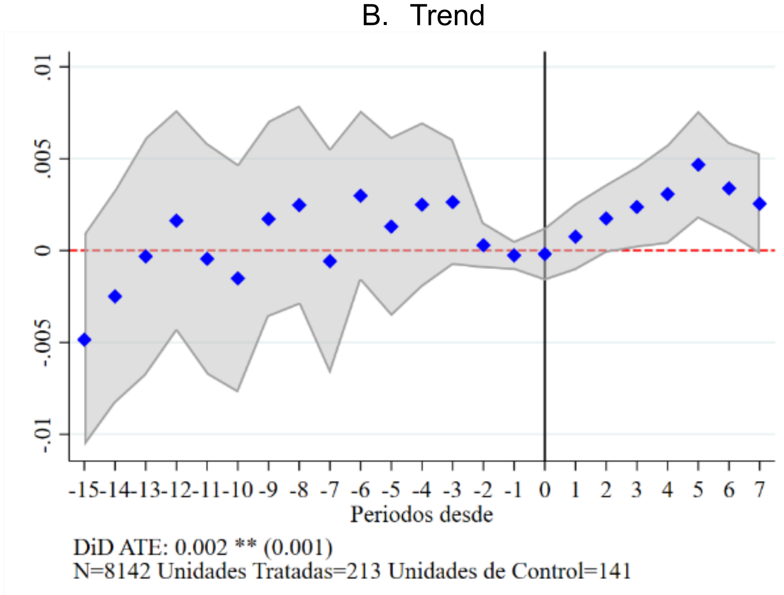
[11] We establish this relationship by estimating an OLS regression where the logarithm of crop yield is regressed on the logarithm of NDVI values for the year 2023 where we can match self-reported yields to remote sensing data. In our baseline specification, we obtain a coefficient of 1.304. Later, we include department fixed effects and control for farm-level characteristics and obtained a coefficient of 1.537.

Figure 6: Effects of Enhanced Irrigation Canals on NDVI

A. Raw Data



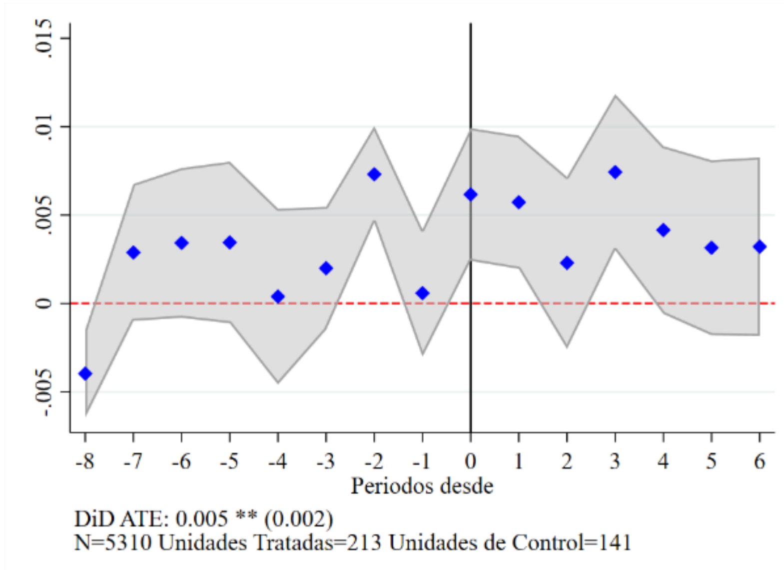
B. Trend



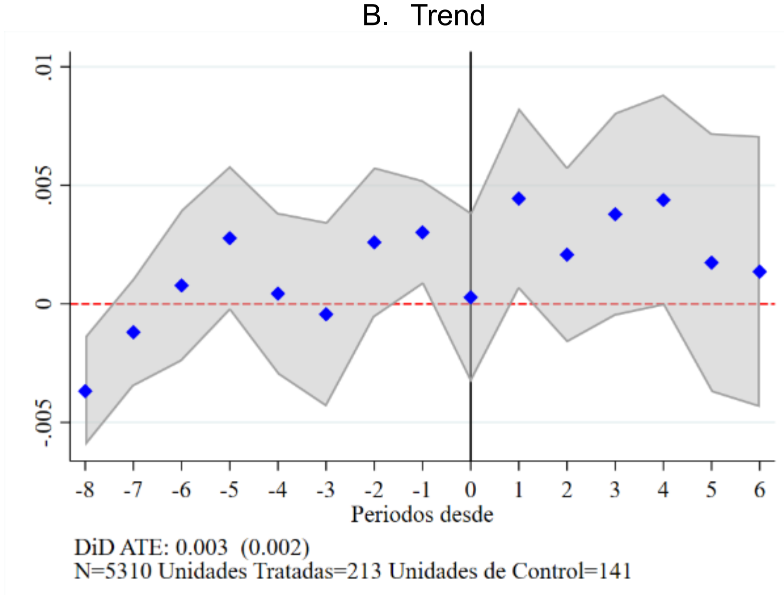
Notes: The figure displays the estimates from a synthetic difference in difference approach as in Arkhangelsky et al. (2021). Panel A shows the raw NDVI series while panel B shows the 12-month moving average.

Figure 7: Placebo Test – Pre-2016 Period with 2009 as Treatment Year

A. Raw Data



B. Trend

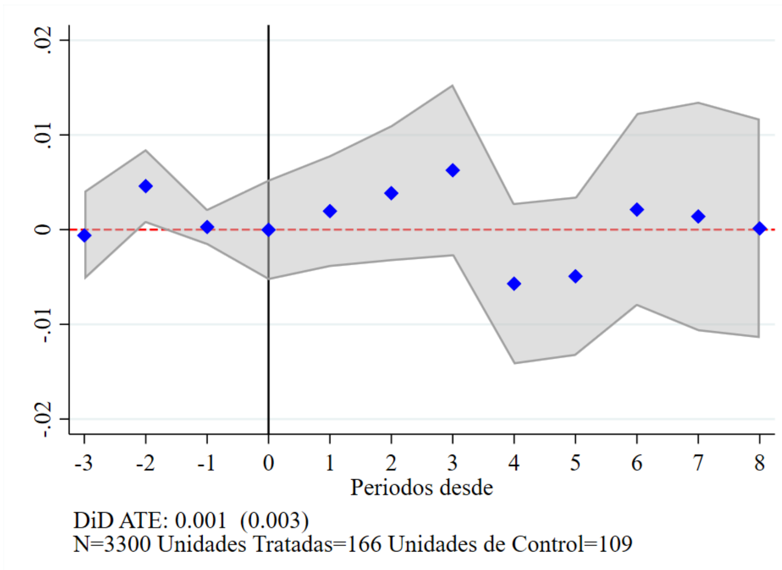


Notes: Similar to Figure 3, but only considers the period before 2016 and sets the post-period treatment in 2009.

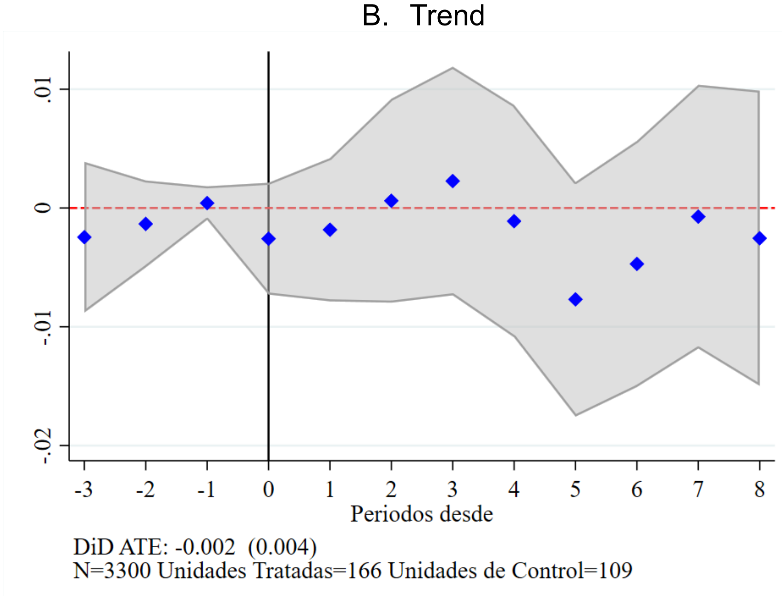
Second, we implement a falsification test by examining outcomes that should remain unaffected by canal rehabilitation. Specifically, we use the Bare Soil Index (BSI), a remote sensing measure designed to detect exposed or non-vegetated soil surfaces by enhancing soil reflectance and minimizing the influence of vegetation. Unlike NDVI, which captures vegetative vigor, BSI contrasts the expected effects of improved irrigation infrastructure. Since the intervention is intended to enhance vegetative growth through improved water access, it should not have a direct impact on BSI values. Due to limitations in data availability, BSI could only be computed for the 2013–2023 period, covering the years immediately before and after the intervention[12].

Figure 8: Effects of Enhanced Irrigation Canals on BSI

A. Raw Data



B. Trend



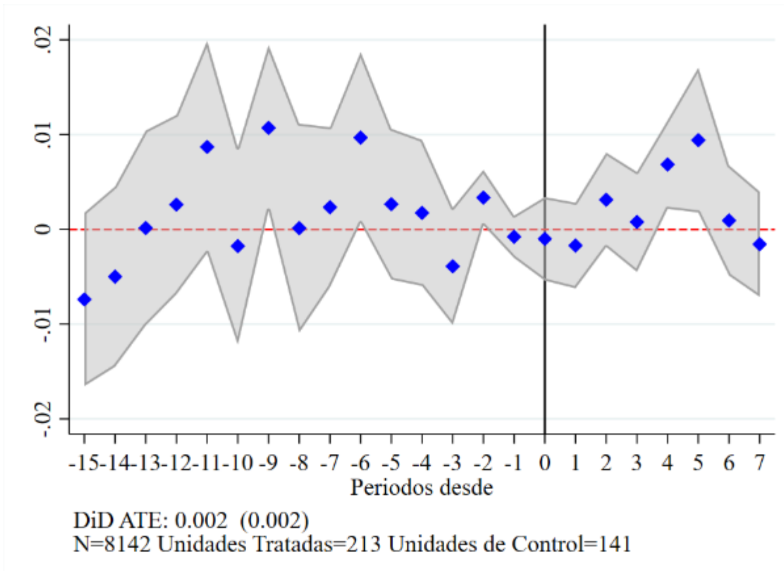
Notes: Similar to Figure 3, but uses BSI as the outcome and focuses on a shorter timeframe (2013–2023)

[12] As an additional robustness check, the Annex A4 replicates the SDID analysis using NDVI as the outcome variable for the 2013–2023 period, the same timeframe covered by the BSI data. The results confirm that the estimated treatment effect remains consistent, indicating that the use of both Landsat 7 and Landsat 8 imagery does not introduce measurement error or bias in the NDVI estimates.

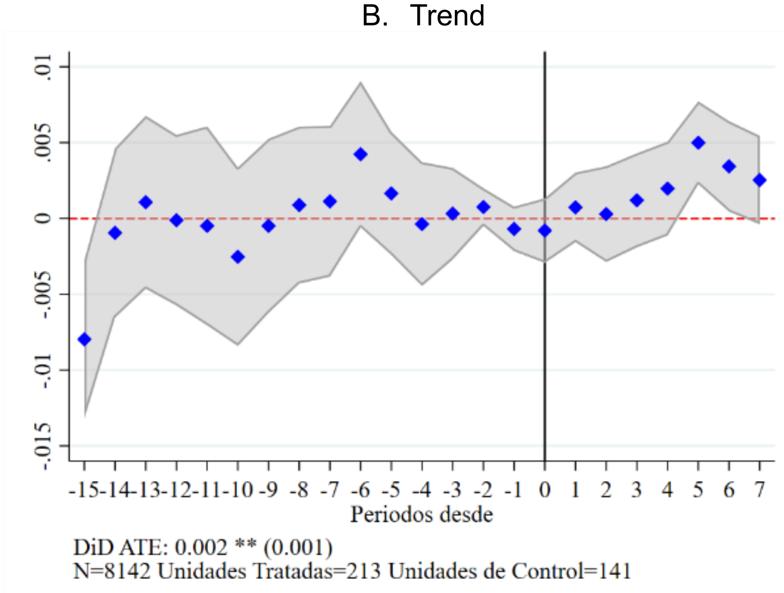
Figure 8 presents the estimated effect of canal rehabilitation on BSI, and the results indicate no statistically significant changes. This supports the validity of our identification strategy by suggesting that the treatment is not spuriously influencing unrelated remote sensing signals or general land surface reflectance patterns.

Figure 9: Robustness to NDVI Measurement – Annual Maximum NDVI

A. Raw Data



B. Trend



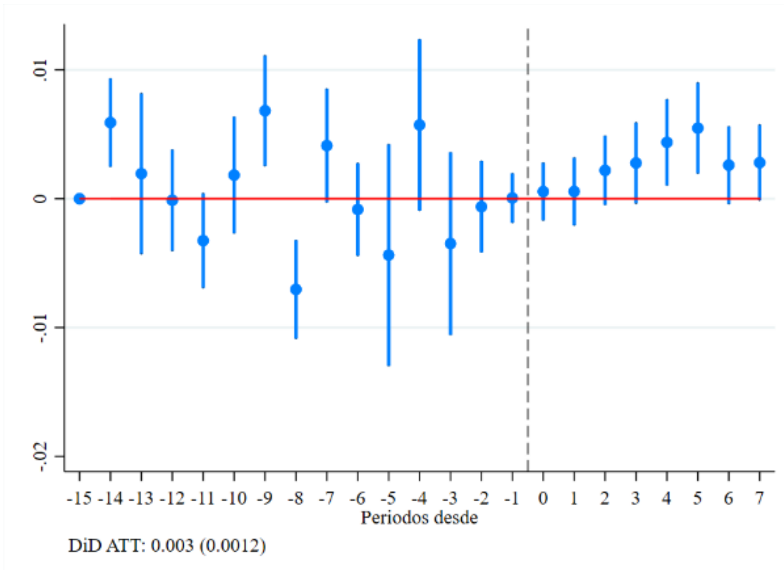
Notes: Similar to figure 3 but uses annual max NDVI instead of mean NDVI.

Next, we test the robustness of our findings to an alternative measure of NDVI by using the annual maximum value instead of the mean. Maximum NDVI focuses on the best observed vegetative condition, offering a robust signal of the crop peak performance. Figure 9 presents the results. The analysis shows a positive trend in the post-rehabilitation period with an average treatment effect of a 0.002 increase in NDVI in the long-term trends, consistent with our preferred measure.

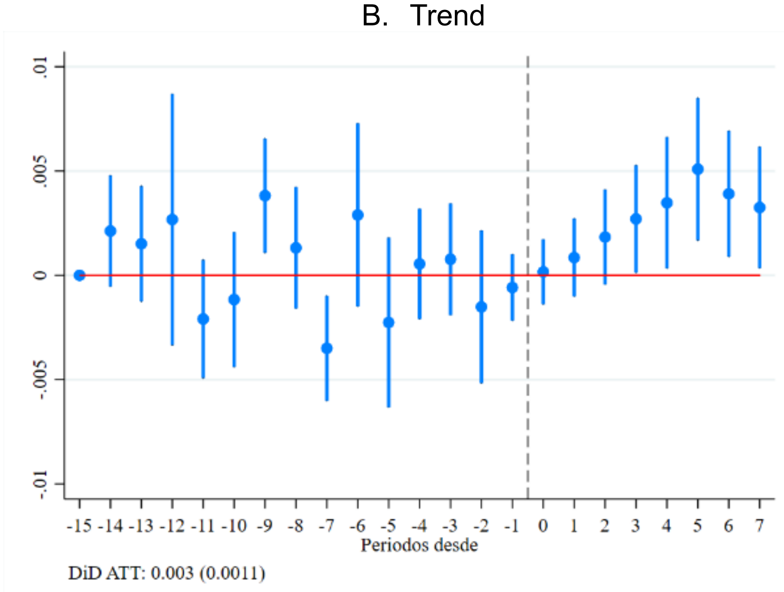
Lastly, we assess whether our results hold when using an event-study difference-in-differences approach instead of the SDID procedure. Figure 10 summarizes these findings. The results from this alternative specification also reveal a positive trend and a statistically significant average treatment increase in NDVI, further confirming the robustness of our estimates.

Figure 10: Robustness to SDID Weighting – Event Study Difference in Difference

A. Raw Data



B. Trend



Notes: Similar to Figure 3, but implements the analysis using an event-study Difference-in-Differences (DiD) approach rather than the Synthetic Difference-in-Differences (SDID) method.

In summary, our analysis indicates that enhanced irrigation canals significantly boost grape production, increase effective irrigated land, and reduce yield losses. These results are further supported by the remote sensing analysis using NDVI, which provides objective evidence of improved vegetation health and enhanced crop yield. Additionally, multiple robustness tests confirm that these findings are not driven by model-specific choices. Together, the evidence suggests that the rehabilitated irrigation infrastructure under PROSAP III has delivered meaningful and long-term benefits to grape productivity in the region, carrying important implications for agricultural policy and future infrastructure investments.

7. Conclusions

This study offers compelling evidence that rehabilitation of irrigation infrastructure can lead to measurable productivity gains in semi-arid agricultural systems. By leveraging a combination of satellite-based NDVI time series that spans 20 years and cross-sectional farmer-level survey data, we provide a robust estimate of the impact of irrigation canal improvements on vineyard performance in Argentina's San Juan province.

Our findings show that canal rehabilitation under the PROSAP III program significantly increased the area under effective irrigation, reduced vulnerability to irrigation-related production losses and significantly improved grape yields among beneficiary farmers. Importantly, these effects persisted and even intensified over time, suggesting that infrastructure investments can generate compounding benefits as farmers adapt and optimize water use.

In the same vein, it can take several years after canal improvements are finalized for farmers to effectively adopt new irrigation techniques and thereby improve their productivity, so impacts may not be fully realized immediately post-treatment. This also underscores the potential of remote sensing as a scalable and objective tool for agricultural impact evaluation for longer study periods. In contexts where traditional monitoring systems are weak or costly to implement, satellite imagery provides a powerful complement to survey data, especially for perennial crops that exhibit seasonal and interannual variability.

The results reinforce the importance of investing in public goods that improve agricultural water management. As governments and multilateral institutions continue to fund large-scale infrastructure projects across Latin America, this study offers a blueprint for how high-frequency, spatially explicit data can be used to rigorously assess impact and guide resource allocation. More broadly, the findings contribute to the global evidence base on the role of irrigation in promoting climate-resilient agriculture, rural livelihoods, and export competitiveness.

While our analysis isolates the impact of canal rehabilitation, it is important to consider how these effects may interact with other complementary investments. Technical assistance and complementary agricultural infrastructure, such as drip irrigation systems or water storage tanks, could amplify the observed gains in productivity (Lopez & Salazar, 2017). In a similar context, Maffioli et al. (2018) evaluate the impact of two complementary projects in Argentina (PROSAP and the *Support Program for Small Producers of the Wine Industry in Argentina,* PROVIAR) and show that financing irrigation infrastructure and additionally providing technical assistance to beneficiary farmers results in higher productive impacts than the sum of the effects caused by separate interventions. This may be the case in the irrigation intervention being studied here, as capacity levels of the different Irrigation Boards and Canal Commissions likely varied, and notably not all the participating organizations expressed interest in receiving support for the technical and administrative management of the improved systems. This could help explain variations in rehabilitation outcomes across canals and departments, as areas with stronger user engagement and clearer maintenance responsibilities would be better positioned to sustain improvements over time. Furthermore, technical assistance activities were not attended by all farmers in the area of influence, which may possibly explain the heterogeneity of impacts. Therefore, understanding how these complementary factors influence outcomes is critical for designing integrated rural development strategies and maximizing the return on infrastructure investments.

Looking ahead, future research could examine heterogeneity in treatment effects—such as by farm size, irrigation system type, or adoption of complementary practices—and explore long-term spillovers to income, land value, and water conservation. Integrating farmer behavior, institutional capacity, and environmental outcomes into the evaluation framework would further enrich our understanding of how rural infrastructure shapes agricultural development.

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). *Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program.* Journal of the American Statistical Association, 105(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746

Acevedo-Opazo, C., Tisseyre, B., Guillaume, S., & Ojeda, H. (2010). The potential of high spatial resolution information to define within-vineyard zones related to vine water status. Precision Agriculture, 11(6), 636–656.

Adeoti, A., Barry, B., Namara, R. E., Kamara, A., & Titiati, A. (2007). Treadle pump irrigation and poverty in Ghana. *International Journal of River Basin Management, 5*(4), 285–292.

Adhikary, S., Biswas, B., Naskar, M. K., Mukherjee, B., Singh, A. P., & Atta, K. (2022). Remote sensing for agricultural applications. In Arid Environment-Perspectives, Challenges and Management. IntechOpen.

Agosta, E., Canziani, P., & Cavagnaro, M. (2012). Regional climate variability impacts on the annual grape yield in Mendoza, Argentina. *Journal of Applied Meteorology and Climatology*, *51*(6), 993-1009.

Alface, A. B., Pereira, S. B., Filgueiras, R., & Cunha, F. F. (2019). Sugarcane spatial-temporal monitoring and crop coefficient estimation through NDVI. Revista Brasileira de Engenharia Agrícola e Ambiental, 23(5), 330-335.

Anastasiou, E., Balafoutis, A., Darra, N., Psiroukis, V., Biniari, A., Xanthopoulos, G., & Fountas, S. (2018). Satellite and proximal sensing to estimate the yield and quality of table grapes. *Agriculture*, *8*(7), 94.

Aramburu, J., Garone, L. F., Maffioli, A., Salazar, L., & Lopez, C. A. (2019). *Direct and spillover effects of agricultural technology adoption programs: Experimental evidence from the Dominican Republic* (No. IDB-WP-971). IDB Working Paper Series.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. American Economic Review, 111(12), 4088-4118.

Aseyehegn, K., Yirga, C., & Rajan, S. (2012). Effect of small-scale irrigation on the income of rural farm households: The case of Laelay Maichew district, central Tigray, Ethiopia. *Journal of Agricultural Sciences, 7*(1), 43–57.

Becketti, S. 2013. Introduction to Time Series Using Stata. College Station, TX: Stata Press.

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., de Abelleyra, D., Ferraz, R., ..., & Verón, S. (2018). Remote sensing and cropping practices: a review. Remote Sensing, 10, 99. doi:10.3390/rs10010099

Berbel, J., & Mateos, L. (2013). Does modernization save water? A meta-analysis of reduction in water demand after irrigation modernization. *Agricultural Water Management, 146*, 370–377.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). *How much should we trust differences-in-differences estimates?* Quarterly Journal of Economics, 119(1), 249–275. https://doi.org/10.1162/003355304772839588

Binswanger, H., Khandker, S., & Rosenzweig, M. (1993). How Infrastructure and Financial Institutions Affect Agricultural Output and Investment in India. Journal of Development Economics, 41(2), 337-366.

Cavatassi, R., González-Flores, M., Winters, P., Andrade-Piedra, J., Espinosa, P., & Thiele, G. (2011). Linking smallholders to the new agricultural economy: The case of the plataformas de concertación in Ecuador. Journal of Development Studies, 47(10), 1545-1573. doi:10.1080/00220388.2010.536221y

Chaves, M. M., Santos, T. P., Souza, C. R., et al. (2010). Deficit irrigation in grapevine improves water-use efficiency while controlling vigour and production quality. Annals of Applied Biology, 150(2), 237–252.

Chivasa, W., Mutanga, O., & Biradar, C. M. (2017). Application of remote sensing in estimating maize grain yield in heterogeneous African agricultural landscapes: a review. International Journal of Remote Sensing. 38, 6816–6845. doi:10.1080/01431161.2017.136539

Clarke, D., Pailañir, D., Athey, S., & Imbens, G. W. (2023). Synthetic difference-in-differences estimation.

Damania, R., Desbureaux, S., Zaveri, E., & Russ, J. (2019). Quality Unknown: The Invisible Water Crisis. Washington, D.C.: World Bank.

Deininger, K., & Xia, F. (2016). Quantifying spillover effects from large land-based investment: The case of Mozambique. *World Development*, *87*, 227-241.

Dercon, S., Gilligan, D., Hoddinott, J. & Woldehanna, T. (2006). The impact of roads and agricultural extension on consumption growth and poverty in fifteen Ethiopian villages. CSAE Working Paper Series 2007-01. Oxford: CSAE.

Dillon, A. (2011). The effect of irrigation on poverty reduction, asset accumulation, and informal insurance: Evidence from northern Mali. World Development, 39(12), 2165–2175.

Dinkelman, T. (2011). The Effects of Rural Electrification on Employment: New Evidence from South Africa. American Economic Review, 101(7), 3078-3108.

Duflo, E., & Pande, R. (2007). Dams. *Quarterly Journal of Economics, 122*(2), 601–646.

Escobal, J., & Ponce, C. (2002). The Benefits of Rural Roads: Enhancing Income Opportunities for the Rural Poor. Working paper, GRADE, Grupo de Análisis para el Desarrollo, Lima, Perú.

Ezimand, K., Chahardoli, M., Azadbakht, M., & Matkan, A. A. (2021). Spatiotemporal analysis of land surface temperature using multi-temporal and multi-sensor image fusion techniques. *Sustainable Cities and Society*, *64*, 102508.

Fan, S. (2008). Public expenditures, growth, and poverty: Lessons from developing countries. Baltimore: Johns Hopkins University Press.

Fan, S., L. Zhang, & X. Zhang (2002). Growth, inequality and poverty in rural China: the role of public investments. Research Report 125. IFPRI, Washington, D.C.

Fan, S., Brzeska, J., Keyzer, M., & Halsema, A. (2008). From Subsistence to Profit: Transforming Smallholder Farms. IFPRI Policy Brief. Washington, D.C.: IFPRI.

FAO. (2021). FAO Statistical Yearbook. Rome: FAO.

Fereres, E., & Evans, R.G. (2006). Irrigation of fruit trees and vines: An introduction. Irrigation Science, 24(2), 55–57.

Garcia-Pedrero, A., Gonzalo-Martín, C., Lillo-Saavedra, M., & Rodríguez-Esparragón, D. (2018). The outlining of agricultural plots based on spatiotemporal consensus segmentation. Remote Sensing, 10(12), 1991.

Gibbons, M.A., Maffioli, A., & Rossi, M. (2016). Money for Wine? Complementarities in the provision of private and public goods to wine producers. Inter-American Development Bank. Strategy Development Division. Series IDB-WP-689

Hall, A., Lamb, D. W., Holzapfel, B., & Louis, J. (2011). Optical remote sensing applications in viticulture—a review. Australian Journal of Grape and Wine Research, 17(2), 159–173.

Hirano, K., & Imbens, G. W. (2001). Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization, Health Services and Outcomes Research Methodology, 2, 259–278. doi:10.1023/ A:1020371312283

Hussain, I., & Hanjra, M. A. (2004). Irrigation and poverty alleviation: Review of the empirical evidence. Irrigation and Drainage, 53(1), 1–15.

Jacoby, H. (2000). Access to markets and the benefits of rural roads. Economic Journal, 110(465), 713-737.

Jara, J., Ortega-Farías, S., & Searles, P.S. (2017). Response of vineyard evapotranspiration and yield components of a Carménère (Vitis vinifera L.) vineyard to different irrigation levels in Central Chile. Irrigation Science, 35(1), 21–29.

Jouanjean, M. A. (2013). Targeting infrastructure development to foster agricultural trade and market integration in developing countries: An analytical review. London: Overseas Development Institute.

Kasimati, A., Espejo-Garcia, B., Vali, E., Malounas, I., & Fountas, S. (2021). Investigating a selection of methods for the prediction of total soluble solids among wine grape quality characteristics using normalized difference vegetation index data from proximal and remote sensing. *Frontiers in Plant Science*, *12*, 683078.

Khandker, S., Barnes, D., Samad, H., & Huu Minh, N. (2008). Welfare Impacts of Rural Electrification: Evidence from Vietnam. World Bank. Washington, D.C.: World Bank.

Khandker, S., Bakht, Z. & Koolwal, G. (2009). The poverty impact of rural roads: the evidence from Bangladesh. Economic Development and Cultural Change, 57, 685-722.

Kinyanjui, M. J. (2011). NDVI-based vegetation monitoring in Mau Forest complex, Kenya. African Journal of Ecology, 49(2), 165-174. doi:10.1111/j.1365-2028.2010.01251.x

Levy, H. (1996). Kingdom of Morocco: Impact Evaluation Report, Socioeconomic Influence of Rural Roads. World Bank, Operation Valuation Department. Washington, D.C.: World Bank.

Lichtenberg, E., & Zilberman, D. (1986). The econometrics of damage control: Why specification matters. American Journal of Agricultural Economics, 68(2), 261–273.

Lillesand, T. M., & Keifer, R.W. (2002). Remote Sensing and Image Interpretation, 4th ed. New York, NY: John Wiley and Sons.

Lipscomb, M., Mobarak, A. M., & Barham, T. (2013). Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. American Economic Journal: Applied Economics, 5(2), 200-231. doi: 10.1257/app.5.2.200

Lyu, H., Grafton, M., Ramilan, T., Irwin, M., Wei, H. E., & Sandoval, E. (2023). Using remote and proximal sensing data and vine vigor parameters for non-destructive and rapid prediction of grape quality. *Remote Sensing*, *15*(22), 5412.

Lobell, D. B., & Field, C. B. (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental research letters*, *2*(1), 014002.

Lobell, D. B., Thau, D., Seifert, C., Engle, E., & Little, B. (2015). *A scalable satellite-based crop yield mapper.* Remote Sensing of Environment, 164, 324–333. https://doi.org/10.1016/j.rse.2015.04.021

Lokshin, M., & Yemtsov, R. (2005). Has Rural Infrastructure Rehabilitation in Georgia Helped the Poor? World Bank Economic Review, 19(2), 311-333. Available at: https://www.jstor.org/stable/40282218

Lopez, C. A., & Salazar, L. (2017). Unraveling the threads of decentralized community-based irrigation systems in Bolivia. *BID (Banco Interamericano de Desarrollo) Working Paper*.

López, R., & Galinato, G.I. (2007). Should governments stop subsidies to private goods? Evidence from rural Latin America. Journal of Public Economics, 91, 1071-94.

Lykhovyd, P. V., Vozhehova, R. A., Lavrenko, S. O., & Lavrenko, N. M. (2022). The study on the relationship between normalized difference vegetation index and fractional green canopy cover in five selected crops. *The Scientific World Journal*, *2022*(1), 8479424.

Maffioli, Alessandro, María Amelia Gibbons, and Martín Rossi 2018. *Support Program for Small Producers of the Wine Industry in Argentina (PROVIAR) and Provincial Agricultural Services Program (PROSAP)*. https://doi.org/10.18235/0001230

Marbler, A. (2024). Water scarcity and local economic activity: Spatial spillovers and the role of irrigation. *Journal of Environmental Economics and Management*, *124*, 102931.Meinzen-Dick, R.

(2007). Beyond panaceas in water institutions. Proceedings of the National Academy of Sciences, 104(39), 15200–15205.

Mu, R., & van de Walle, D. (2008). Rural Roads and Local Market Development in Vietnam. World Bank. Washington, D.C.: World Bank.

PROSAP-IICA (2011). *Project "Improvement of the secondary irrigation network" of the Agricultural Development Project and Management of the Irrigated Area: Canal del Norte–25 de Mayo, Province of San Juan: Project document* [Unpublished internal report]. Provincial Agricultural Services Program (PROSAP) and Inter-American Institute for Cooperation on Agriculture (IICA).

Ricce, W. D. S., Caramori, P. H., & Roberto, S. R. (2013). Potencial climático para a produção de uvas em sistema de dupla poda anual no Estado do Paraná. *Bragantia*, *72*, 408-415.

Rosegrant, M.W., Cai, X., & Cline, S.A. (2009). World Water and Food to 2025: Dealing with Scarcity. Washington, D.C.: IFPRI.

Rosenbaum, P. R. (2002). *Observational Studies* (2nd ed.). Springer. https://doi.org/10.1007/978-1-4757-3692-2

Rosenbaum, P. R. (1987). Model-based direct adjustment. Journal of the American Statistical Association, 82, 387–394. doi 10.1080/01621459.1987.10478441

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Rossi, M. (2013). Evaluación de impacto de proyectos de Riego en Mendoza. UCAR-Unidad de Seguimiento y Evaluación. Documento interno.

Rossi, M. (2016). Evaluación de impacto de proyectos de Riego en Mendoza y San Juan. UCAR-Unidad de Seguimiento y Evaluación. Documento interno.

Salazar, L., Palacios, A. C., Selvaraj, M., & Montenegro, F. (2021). Using satellite images to measure crop productivity: Long-term impact assessment of a randomized technology adoption program in the Dominican Republic (No. IDB-WP-01234). IDB Working Paper Series.

Saleth, R. M., & Dinar, A. (2004). The Institutional Economics of Water: A Cross-Country Analysis of Institutions and Performance. Cheltenham: Edward Elgar.

Schling, M., & Pazos, N. (2022). The impact of smart subsidies on agricultural production: Innovative evidence from Argentina using survey and remote sensing data (No. IDB-WP-01358). IDB Working Paper Series.

Sills, E. O., Herrera, D., Kirkpatrick, A. J., Brandao Jr., A., Dickson, R., Hall, S., … Pfaff, A. (2015). Estimating the impacts of local policy innovation: the synthetic control method applied to tropical deforestation. PLoS ONE, 10(7), e0132590. doi: 10.1371/journal.pone.0132590

Sun, L., Gao, F., Anderson, M.C., Kustas, W.P., Alsina, M.M., Sanchez, L., & Post, K. (2017). Daily mapping of 30 m LAI and NDVI for grape yield prediction in California vineyards. Remote Sensing, 9(4), 317.

van de Walle, D., & Cratty, D. (2002). Impact evaluation of a Rural Road Rehabilitation Project. World Bank Working Paper No. 44472. Washington, D.C.: World Bank.

Ward, F.A., & Pulido-Velazquez, M. (2008). Water conservation in irrigation can increase water use. Proceedings of the National Academy of Sciences, 105(47), 18215–18220.

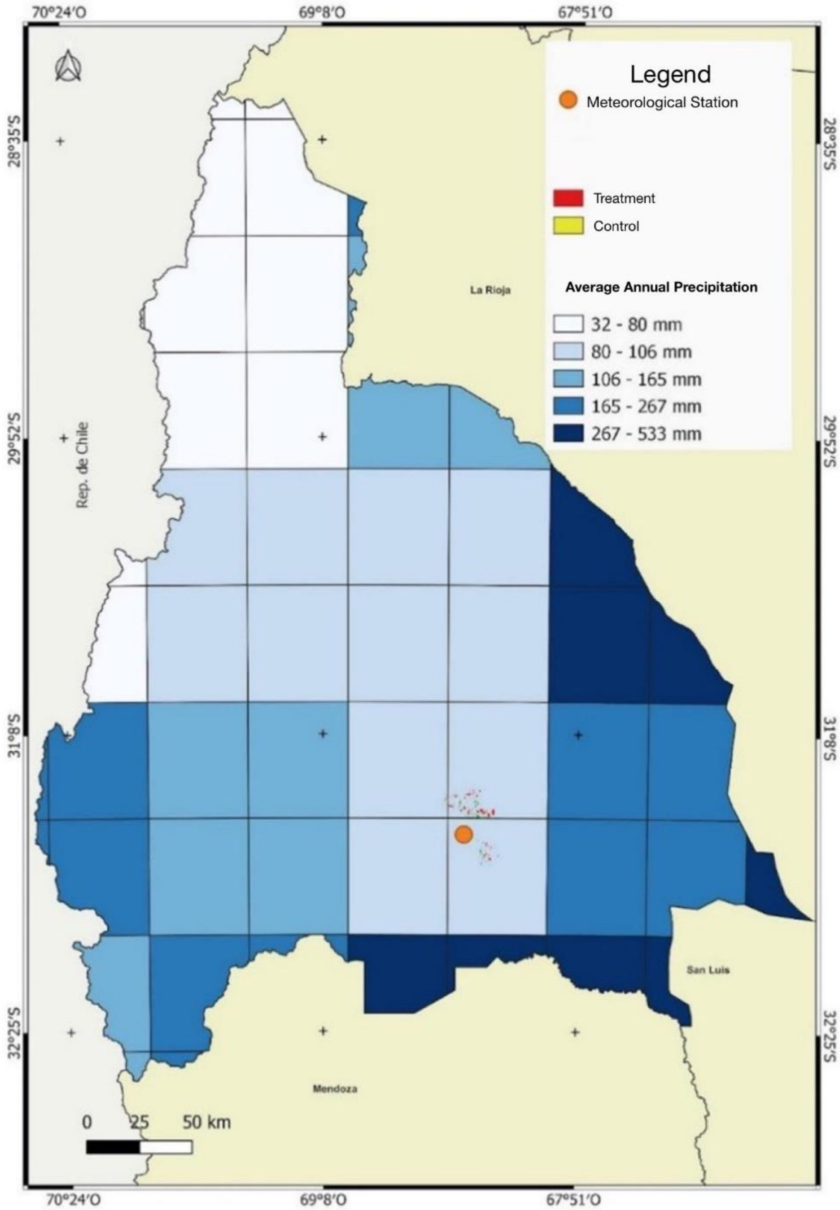
World Bank. (2007). Making the Most of Scarcity: Accountability for Better Water Management Results in the Middle East and North Africa. Washington, D.C.: World Bank.

Annex

Figura A.1

Notes: This image shows the processing involved to isolate cultivated parcels for each farm.

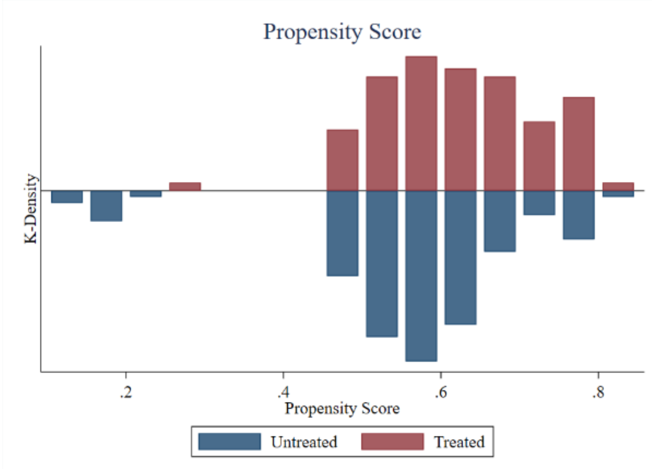
Figura A.2



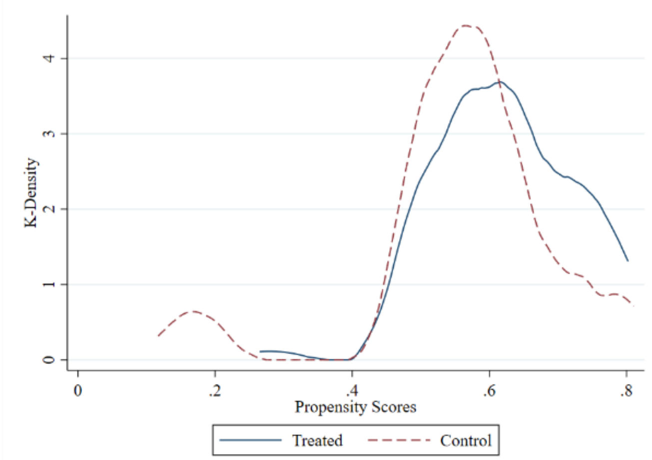
Notes: This image shows the cummulative precipitation received by each distict region. The area of intervention is located in an area that received between 90-106 mm.

Figure A3: Distribution of Propensity Scores

A. Propensity Score Support



B. Propensity Score Matching



C. Propensity Score After Matching

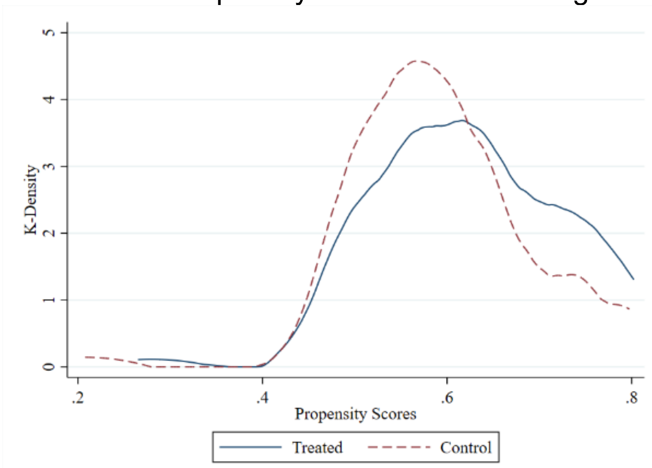
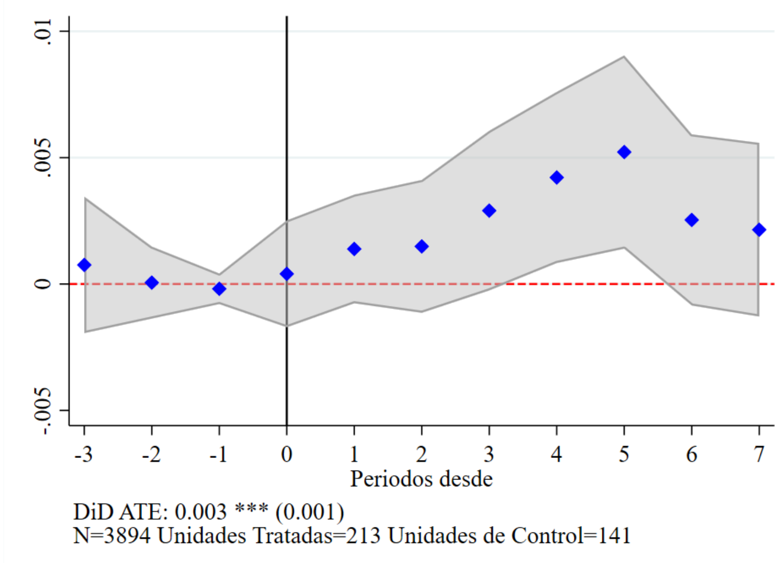
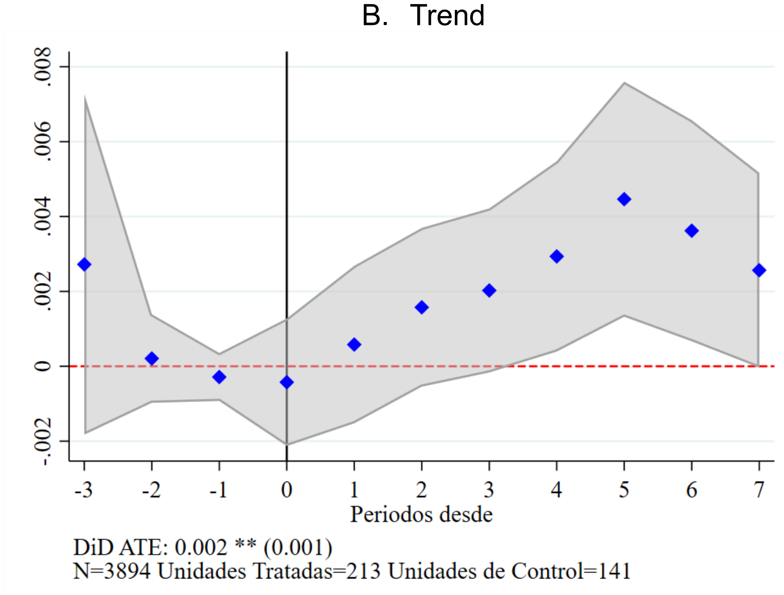


Figure A4: Effects of Enhanced Irrigation Canals on NDVI – Short Period 2013-2023

A. Raw Data



B. Trend



Notes: Similar to Figure 3 but uses annual NDVI for the 2013-2023 period.

Appendix A5: Event Study Difference-in-Differences Specification

As a robustness check to the main analysis using a Synthetic Difference-in-Differences (SDiD) approach, we implement an event study Difference-in-Differences (DiD) specification. The event study framework is a widely used extension of the standard two-period DiD estimator that enables the analysis of treatment effects over multiple periods before and after an intervention (Jacobson, LaLonde, and Sullivan 1993; Autor 2003). This approach allows for a dynamic assessment of treatment effects and is particularly useful in settings where the timing of the intervention is known and staggered or where treatment effects may evolve over time.

In addition to capturing the trajectory of impacts following the intervention, the event study design facilitates a direct test of the parallel trends assumption, which underpins causal identification in DiD settings (Angrist and Pischke 2009; Borusyak and Jaravel 2017). By estimating pre-treatment coefficients, we can examine whether treated and control units exhibited similar trends prior to the intervention, thereby strengthening the credibility of the identification strategy. In our context, we use this framework to investigate the timing and persistence of the effects of irrigation infrastructure improvements on grape yields, using remotely sensed NDVI (Normalized Difference Vegetation Index) as a proxy for vine vigor and productivity.

We estimate the following two-way fixed effects model with event-time indicators:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{\substack{k=-15, \\ k\neq -1}}^{7} \beta_k * Treated_i * 1\{k = t\} + \gamma' X_{it} + \epsilon_{it}$$

Where Y_{it} denotes the NDVI value for plot *i* in year *t*, α_i are plot fixed effect controlling for time-invariant unobserved heterogeneity, and λ_t are year fixed effect capturing common shocks across units. X_{it} is a vector of controls including average temperature and precipitation. The term $Treated_i$ indicates whether plot *i* is ever treated, and 1{k=t} is an indicator for event time *k*, where *t* is the treatment year for plot *i*. We omit the event time indicator for k=1, which serves as the reference period.

This specification enables visualization of the dynamic effects of the intervention. In addition, the significance and magnitude of pre-treatment coefficients (k<0) provide a diagnostic for the validity of the parallel trends assumption. Post-treatment coefficients (k≥0) reveal how the irrigation rehabilitation affected productivity over time and whether effects persisted, grew, or dissipated in the years following implementation.

References

- Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
- Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21(1), 1–42.
- Borusyak, K., & Jaravel, X. (2017). Revisiting Event Study Designs: Robust and Efficient Estimation. Working Paper.
- Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 83(4), 685–709.