01/2023

DEval DISCUSSION PAPER

DOES IRRIGATION STRENGTHEN CLIMATE RESILIENCE?

A Geospatial Impact Evaluation of Interventions in Mali

2023

Ariel BenYishay
Seth Goodman
Rachel Sayers
Kunwar Singh
Madeleine Walker
Mascha Rauschenbach
Martin Noltze

DEval
GERMAN
INSTITUTE FOR
DEVELOPMENT
EVALUATION

IMPRINT

Published by

German Institute
for Development Evaluation (DEval)
Fritz-Schäffer-Straße 26
53113 Bonn, Germany

Phone: +49 (0)228 33 69 07-0
E-mail: info@DEval.org
www.DEval.org

Authors

Ariel BenYishay, AidData
Seth Goodman, AidData
Rachel Sayers, AidData
Kunwar Singh, AidData
Madeleine Walker, AidData
Mascha Rauschenbach, DEval
Martin Noltze, DEval

Bibliographical reference

BenYishay A., S. Goodman, R. Sayers, K. Singh, M. Walker, M. Rauschenbach and M. Noltze (2023), *Does Irrigation Strengthen Climate Resilience? A Geospatial Impact Evaluation of Interventions in Mali*, DEval Discussion Paper 1/2023, German Institute for Development Evaluation (DEval), Bonn.

This paper has been published in PNAS Nexus by Oxford University Press.
Citation: BenYishay, A.; Sayers, R.; Singh, K.; Goodman, S.; Walker, M.; Traore, S.; Rauschenbach, M. and M. Noltze (2024), Irrigation Strengthens Climate Resilience: Long-term Evidence from Mali Using Satellites and Surveys, PNAS Nexus, Volume 3, Issue 2, *https://doi.org/10.1093/pnasnexus/pgae022*

ISBN 978-3-96126-187-1 (PDF)

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In contrast to our evaluation reports, they do not contain any direct recommendations for German and international development organizations.

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Abstract

Agriculture in the Sahel is largely rainfed, and the rural economy is strongly dependent on rainfall patterns. The current and future impacts and risks associated with climate change are increasingly affecting rural communities in the region. Direct impacts include less predictable rainfall patterns and rising temperatures, which increase the amount of water needed for agricultural production. The broader impacts are threats to the social, economic and ecological resilience of rural communities calling for climate change adaptation.

We assess to what extent irrigation can strengthen the climate resilience of rural communities. Our study sample consists of nearly 1 000 distinct locations in Mali in which small-scale, river-based irrigation and stored-rainwater-based irrigation was introduced over the past two decades. These interventions take place in a context of worsening climate conditions and an armed conflict. The staggered roll-out of irrigation, and repeated observations over 20 years, allows us to compare the pre- and post-irrigation outcomes of locations while adjusting for confounding factors. We geospatially link data on irrigation interventions with measures of agricultural production using high-resolution satellite imagery and surveys, along with data on child nutrition and health outcomes, and conflict event data.

We find that the introduction of irrigation led to substantial increases in agricultural production on nearby fields, with these gains persisting even a decade later. Children in nearby communities are less likely to be stunted or severely underweight due to the irrigation, and conflict risks decrease in the closest communities. Some of these gains are offset by worsening conditions farther away from the newly installed irrigation. These findings suggest that, even with political conflicts in semi-arid areas already increasing, sustainable irrigation may offer a particularly valuable tool to improve communities' resilience toward present and future negative socio-economic impacts of climate change.

Key words: irrigation, climate, resilience, geospatial impact evaluation, Mali, Sahel

About this DEval Discussion Paper

The discussion paper is part of the DEval evaluation of interventions for climate change adaptation. This paper focuses on an existing evidence gap on the effectiveness, impact and sustainability of irrigation infrastructure interventions for strengthening climate resilience and climate change adaptation in the nexus of agriculture and water. The evaluation selected the long-term investments of German financial and technical development cooperation in Mali as a representative learning case for similar interventions in the context of climate vulnerability and conflict in the African Sahel region.

Acknowledgements

The evaluation team was supported by numerous individuals and organisations in their work.

First and foremost, the authors thank the members of the reference group of DEval’s evaluation of interventions for climate change adaptation, including the Federal Ministry for Economic Cooperation and Development (BMZ) and the International Climate Initiative (IKI) under the leadership of the Federal Ministry for Economic Affairs and Climate Action, in close cooperation with its founder, the Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection and the Federal Foreign Office, the Zukunft – Umwelt – Gesellschaft (ZUG) gGmbH, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) gGmbH and KfW Development Bank (KfW) for their support. The authors especially thank KfW for their invaluable support in data collection and the substantial comments provided. Without this support, the evaluation work would not have been possible.

Finally, the authors are grateful for the critical questions, conceptual impulses, technical support and feedback provided by our colleagues from DEval (Kai Rompczyk, Ezra Bender, Sven Harten, Dirk Hoffmann, Kevin Moull and Georg Kühltau). The AidData team thanks Camila Baioni, Kelsey Marshall, Daisy Garner and Patrick Salsburg for their geocoding and translation support.

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Abbreviations and Acronyms

ACLED	Armed Conflict Location & Event Data Project
BMZ	Federal Ministry for Economic Cooperation and Development
DHS	Demographic and Health Survey
DID	difference-in-difference
EAC-I	Enquête Agricole de Conjoncture Intégrée aux Conditions de Vie des Ménages
FCFA	Franc de la Communauté financière africain
GDC	German development cooperation
GDP	Gross domestic product
GEE	Google Earth Engine
GEP	Google Earth Pro
GIE	Geospatial impact evaluation
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GTD	Global Terrorism Database
HR	High resolution
IPRODI	Irrigation Projects – Inner Delta
IPV	Intimate partner violence
IRRIGAR	Initiative de Renforcement de la Résilience par l'Irrigation et la Gestion Appropriée des Ressources
KfW	KfW Development Bank
LSMS	Living Standards and Measurement Survey
NDDI	Normalised difference drought index
NDVI	Normalised difference vegetation index
NDWI	Normalised difference water index
NIR	Near-infrared
PIM	Périmètre d'irrigation maraicher
PIV	Périmètre irrigué villageois
SD	Standard deviation
SE	Standard errors
SCAD	Social Conflict Analysis Database
SWIR	short-wave infrared
UCDP-GED	Uppsala Conflict Data Program - Georeferenced Events Dataset
USAID	United States Agency for International Development
VHR	very high-resolution
WARICC	Water-Related Intrastate Conflict and Cooperation

1. INTRODUCTION

Agriculture in the Sahel and much of sub-Saharan Africa remains to a large extent rainfed. At the same time, climate variability and possibly change are already causing less predictable rainfall patterns in the region, while rising temperatures increase the amount of water needed for agricultural production. Climate change, resulting in rising temperatures and a shifting precipitation regime, is anticipated to worsen agricultural conditions in the coming decades in the Sahel. Mali for instance, depending on the evolving Representative Concentration Pathway scenario, may experience temperature rises ranging from 2.0 to 4.6°C by 2080. With a high degree of certainty, the number of days with temperatures exceeding the physiological threshold for human adaptability of 35°C[1] is going to increase, potentially resulting in 59 more days in 2080 compared with 2000 (PIK, 2020). One of the consequences of this will likely be a dramatic increase in evaporation and thus the need for irrigation. Whereas the global temperature trend increases constantly with a high degree of certainty, the projections for precipitation are noticeably more erratic. Climate models for Mali, for example, indicate a wide range of possible developments (PIK, 2020). In general, the sparseness of data on precipitation in the region makes precise projections difficult (Otto et al., 2020). However, significant inter-annual variability in precipitation has already been observed (Traore et al., 2013). Aside from yearly average values, estimates for concrete precipitation events depict heavy rainfall becoming more frequent in the Sahel region (Niang et al., 2014), whereas the north of Mali in particular – where most of the projects studied here are located – will receive less precipitation (USAID, 2018). Parallel to this, a significantly increasing number of dry days during the growing seasons will negatively affect crop yields (Traore et al., 2013).

The rural economy of Mali is strongly dependent on annual rainfall patterns and hence fluctuates with climate variability (Zwarts et al., 2005). Agriculture accounts for 39% of Mali's gross domestic product (GDP) (and employs 63% of the workforce), and the majority of the production is exclusively rainfed (Hegazi et al., 2021). Agricultural production is dominated by cotton as the main cash crop, while grains such as rice, millet, sorghum and wheat constitute the main food crops. Mali's population sustains itself on small-scale, rainfed subsistence agriculture and pastoralism. Precipitation events have been erratic in recent years. Already observable changes and existing future projections are underlining the need for agriculture to become less dependent on rainfall fluctuations. In addition to these challenging environmental conditions, recurring conflicts pose an additional obstacle to economic development. Since the country's independence in 1960, a multitude of multidimensional conflicts have taken place, massively affecting parts of the country (Hegazi et al., 2021). This complex setting further reinforces the need to find solutions to climate-induced vulnerabilities.

As a crucial enabler, irrigation has the potential to contribute to adaptation to climate change by providing farmers with access to water during times of scarcity. Many donors, including Germany, have attempted to foster agricultural production in order to contribute to food security and to income increases, to lift farmers and their families above the poverty line and to promote social stabilization in the conflict-affected country. German development cooperation (GDC) has supported irrigation projects in Mali since the late 1990s. More recently GDC has set the objective to help farmers and their communities adapt to climate change through these irrigation interventions. However, project evaluations so far have been confined to assessing the short-term effects of the interventions. This evaluation assesses the extent to which GDC-funded irrigation interventions sustainably contribute to making farmers in Mali and their communities more climate resilient.

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[1] ≥ 35°C is a meteorological threshold above which days are classified as *extremely hot days* (Pongrácz and Bartholy, 2006).

1.1 Contributing to existing research and evaluation

This geospatial impact evaluation assesses the effects of three types of irrigation interventions – small-scale pump-based irrigation, large-scale gravitation-based irrigation, and the valorisation of floodplains for strengthening climate resilience. It makes use of geocoded project locations, remote-sensing data and geocoded survey data.

Our study makes several important contributions. First, we advance extant evaluations by developing and testing theoretical expectations of irrigation infrastructure interventions for climate change adaptation and climate resilience strengthening. Introducing irrigation in small-scale farming has great potential for making rural communities less dependent on climatic fluctuations, most prominently fluctuations in precipitation (Ali and Erenstein, 2017; Amare and Simane, 2018; Bandyopadhyay et al., 2007; Bryan et al., 2011; Gbetibouo, 2009, p. 52; Iheke and Agodike, 2016; Okada et al., 2015). Yet, past evaluations of irrigation interventions in the agricultural sector have focused on outcomes such as food security levels and levels of poverty (Amare and Simane, 2018; Bryan et al., 2011) without making explicit the link with adaptation to climate change.

Second, rigorous impact evaluations and stakeholders' project evaluations in the field of small-scale agriculture have mainly explored short-term effects of these projects (KfW, 2020). Only a few have explored more long-term effects (Strobl and Strobl, 2011). However, an exploration of project-level effects two or four years after project completion is insufficient to assess whether vulnerabilities have permanently been reduced and whether farming communities have become resilient in dealing with future climate shocks and stressors. Studying the effects on adaptation to climate change adds an extra layer of difficulty. Short-term effects that seem to make a positive contribution might turn out to be inadequate strategies for adapting to future climate conditions and may even lead to maladaptation. We advance past research by looking at longer time frames, a large number of project sites, and by explicitly addressing questions related to the sustainability of irrigation impacts.

Third, we provide one of the rare studies of the impacts of irrigation interventions in the context of armed conflict. To the best of our knowledge, only one impact study so far has evaluated the effect of irrigation in a conflict-ridden setting, focusing on the rehabilitation of irrigation infrastructure in Afghanistan (BenYishay et al., 2021). While the risks associated with evaluating irrigation interventions on the ground in an insecure context are evident, the lack of evidence from such contexts is nonetheless problematic, as transferring insights from non-conflict to conflict contexts is not straightforward. The conflict may limit the effectiveness of intervention measures, by directly interrupting project activities (e.g. attacks on infrastructure, intimidation, forced migration of farmers) or by increasing the risk of future losses, which may make farmers hesitant to invest in increasing agricultural productivity and to adopt new technologies. At the same time, the conflict may cause loss of harvests (among many other negative consequences on rural livelihoods) and so further aggravate climate-induced vulnerabilities, emphasising the need for interventions to foster agricultural productivity and assure food security. Lastly, the intervention might also aggravate the existing conflict by, for example, creating disputes over the allocation of land to be irrigated. Conducting a geospatial impact evaluation of irrigation interventions in Mali allows us to assess impacts with reasonable rigour in a context where data collection on the ground would not be feasible due to security concerns. Lastly, by integrating geocoded conflict data from the Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al., 2010) and the Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012) into our statistical models, we can further assess whether and to what extent project success is affected by ongoing conflict and to estimate potential effects of the intervention on conflict risk and intensity.

Fourth, our study adds to the young but growing field of geospatial impact evaluations (GIEs). It advances existing studies using this methodology by focusing on longer time frames than most GIEs[2]

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[2] For an exception of a GIE studying comparatively long-term effects of dams see (Strobl and Strobl, 2011).

and by using a multitude of sources of remote sensing data that allow for triangulation and the production of robust results of the effects of irrigation.

1.2 Strengthening resilience through irrigation

Climate risks and irrigation

The objectives of GDC engagement in the agricultural sector in Mali have been to contribute to food security, the reduction of poverty and to peace-building with the help of irrigation. More recently, GDC added the target of climate change adaptation for dealing with climate risks. Climate risks result from the interaction of vulnerability (of the affected system), its exposure over time (to the hazard), as well as the (climate-related) hazard and the likelihood of its occurrence (IPCC, 2022). In the case of farming communities in rural Mali, droughts and erratic rainfall may lead to harvest failure and losses. For example, a significant positive correlation between rainfall and maize harvests has been observed and, furthermore, a negative relationship between the number of dry days during the rainy season and cotton yields. The farming communities are exposed to these risks as they cannot easily move their agricultural activity elsewhere (where they do not possess land, for example). In addition, hazards such as droughts or erratic rainfall are most likely not confined to specific areas (exposure). The communities are also very sensitive to these negative consequences of climate variability and/or change as their agricultural production is their most important source of food security and income (Bodian et al., 2020). Decreases in food security and income may entail other negative impacts such as worsening health conditions (IPCC, 2014: 5) and an increase in conflict risk and intensity (Humphreys and Weinstein, 2008; Miguel et al., 2004). In addition, these climate risks may negatively impact gender equality, as women are particularly climate-vulnerable,[3] and of course also entail negative environmental impacts such as losses in biodiversity. Irrigation based on river water and stored rainwater has the potential to reduce farmers' sensitivity to droughts and erratic rainfalls and to buffer against the outlined negative socio-economic impacts of climate variability and climate change.

The evaluation covers 978 project sites from different project components that were financed and put in place between 1999 and 2020. Over this time frame, the GDC agencies of KfW (KfW, financial cooperation) and the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ, technical cooperation), supported by AHT Consulting, implemented a range of infrastructure interventions in northern Mali. These interventions can be grouped into pump-based irrigation and the valorisation of flood plains. Pump-based irrigation uses river water only. Water is pumped from the Niger and its tributaries onto close-by fields. We assess two types of plots that are irrigated through pump-based irrigation: the *périmètre d'irrigation villageois* (PIV) where mainly rice is cultivated, and the *perimètre d'irrigation maraicher* (PIM) (market gardens), where women cultivate vegetables. Floodplains, *mares*, fill with rainwater in times of heavy rain or with river water when the river floods. This water is stored and used to irrigate close-by fields (through canals) outside the rainy season, and is thereby given a value it did not previously have.[4]

There are many accompanying measures that complement the setting up, repair and maintenance of these types of irrigation infrastructure, such as building small roads to facilitate the marketing of the produce. Figure 1 illustrates the main activities and the theorised impact chains that lead to higher-level impacts on food security, income, health, reduction of conflict and the improvement of environmental conditions. The graphic illustration of the theory of change and the description of the impact pathways in Chapter 2 are based on the intervention logics/logframes retrieved from project documentation, and on research on the (potential) effects of similar interventions. Our theoretical

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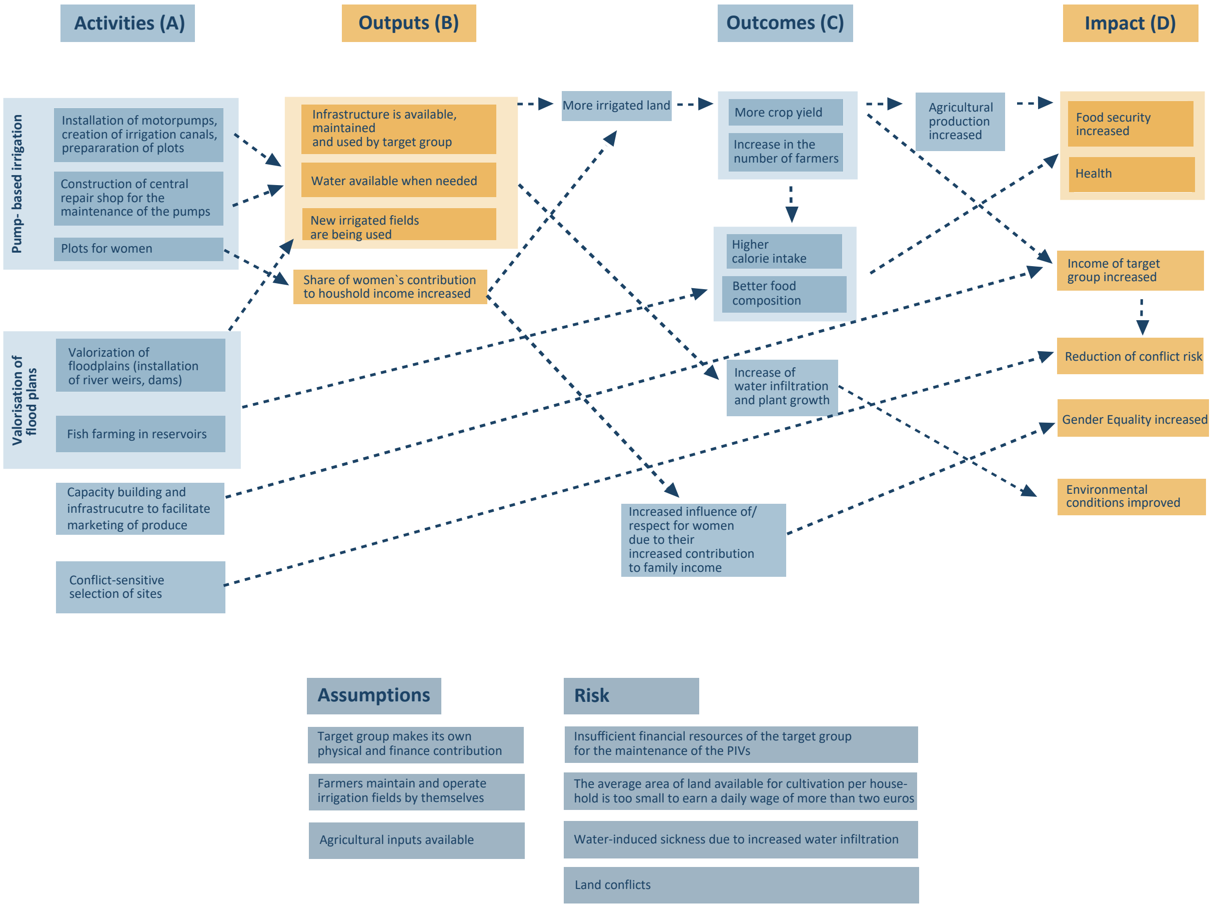
[3] For a more nuanced discussion see 2.3.

[4] Another type of irrigation practised in the Office du Niger in Mali (and also partly funded by German development cooperation) is large-scale gravitation-based irrigation. Here, water flows by gravitation (no pumps involved) through a system of primary, secondary and tertiary canals onto larger fields. Due to data constraints, we do not assess this type of river-based irrigation.

claims, formulated as hypotheses, are situated on the impact level. However, in order to investigate the potential mechanisms between irrigation and different impacts, we also formulate some testable implications on the output and outcome level (see footnotes in Chapter 2).

Figure 1 Theory of change



Source: authors' own figure

From the reduction of vulnerability to climate resilience

In accordance with IPCC (2022) we understand climate resilience as the capacity of human and natural systems to learn, adapt and transform in response to risks induced or exacerbated by climate variability and change. Climate risks are a function of the interaction between environmental hazards triggered by climate variability and change, the exposure of human, natural and infrastructure systems to those hazards and the systems' vulnerabilities. Climate resilience is a component of the broader concept of resilience. With strengthened climate resilience, people and communities will also be more resilient to other types of risks, for instance those that are economic or health-related in nature. A key approach to strengthening climate resilience is climate change adaptation. This is the process of adjustment of human and natural systems to actual and expected adverse effects of climate variability and change (IPCC, 2018).

Vulnerability is the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (IPCC, 2014: 5). While several views on the nexus between vulnerability and resilience exist,[5] we opt for a procedural/temporal approach, where vulnerability forms a pre-disaster condition and resilience refers to the response actions to climate impacts (hazards). Climate resilience adds a time dimension to the concept of vulnerability: a system is resilient when it is less vulnerable to shocks across time, and can recover from them (Gitz and Meybeck, 2012: 26).

If the irrigation projects studied have been effective in building beneficiary households' resilience capacities, the types of responses put in place by households in treatment locations should differ from those in control areas. They should show a lower propensity to adopt detrimental (maladaptive) responses and a higher propensity to adopt positive (adaptive, transformative) responses. In order to strengthen resilience, the intervention needs to reduce vulnerability in the first place. The distinction we make is that impacts that contribute to resilience are more long-term strategies.

We assess the extent to which the interventions under study strengthen the economic, social and ecological resilience of farming communities and their livelihoods by sustainably alleviating negative economic, social and ecological impacts of climate variability and change. Empirically, we assess whether the interventions lead to ameliorations in agricultural production, food security, health, gender equality, conflict and environmental conditions. However, as the impacts of climate change materialise, today's improvements might turn out to be alleviations of climate-change-induced downward trends in these outcomes.

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[5] See Joakim, Mortsch, and Oulahen (2015) for a review.

2. THEORETICAL EXPECTATIONS

2.1 Food security and health

Calorie intake per capita in Mali is one of the lowest in the world, with a prevalence of undernourished people fluctuating at a high level of around 6% (KfW, 2020). Due to the conflict, GDP shrank significantly between 2010 and 2015, accompanied by a sharp rise in wasting and "stunting" among children (KfW, 2020). Most rural dwellers rely for their food on subsistence agriculture (Bodian, Tobie and Marending, 2020) and it is almost entirely dependent on rainfall (Nkonya, Kato and Ru, 2020). Increasing climate fluctuations and the expected impacts of climate change put food security of subsistence farmers further at risk.

GDC in Mali has the objective of reducing the vulnerability of farmers to the absence of and fluctuations in precipitation by making water available for irrigation, independent from rainfall. Under the assumption that the irrigation system is running and maintained, farmers use the newly available water to irrigate the additional plots they are allocated, so that the immediate potential outcomes of the projects are an increase in the area irrigated and in the number of farmers benefiting from irrigation in the locality. In addition, farmers benefiting from the irrigation projects should have a higher likelihood of an extra growing and harvesting season in the dry spell. All these possible developments on the output and outcome level should lead to an increase in agricultural production in general and crop yield in particular. Under the assumption that the increases in yields and production are substantial enough to cover household needs (AfDB, 2019), the irrigation projects are then expected to increase food security in the target community on the impact level (Perez et al., 2015).

H1a: Households in treatment locations are more food secure than those in control locations.

In addition to increasing calorie intake, the interventions could also potentially contribute to better food composition. The intervention type "valorisation of mares", for example, includes fish farming in reservoirs; the consumption of fish is supposed to add variation to farming families' diet. Similarly, some of the locations using pump-based irrigation reserve plots for vegetable cultivation (farmed by women), complementing the predominant crop of rice in the projects.

H1b: Households in treatment locations show a better food composition than those in control locations.

Better food security and, potentially linked to this, better health reduces climate vulnerability by making farming communities less vulnerable to future loss of harvests (caused by droughts, extreme rain events or flooding). Whether the irrigation projects sustainably increase the communities' resilience will depend on the durability of the positive effects on food security and health and is an empirical question.

Improvements in food security and composition have an impact on child nutrition and health, in particular, and the effects of an increase in the quantity or quality of calories are often initially observable among children. This is the case for two reasons. First, since children are still growing, positive changes in their food security and food composition often have larger observable effects in terms of a lessening in stunting, wasting, and mortality than among adults. Second, positive nutritional changes often accrue to an observable effect more quickly among children than adults, as short-term investments have a greater potential for impact. There is a broad strand of the literature that points out positive effects of increases in income and food security on child health (Fernald et al., 2008; Mary et al., 2020). Maccini and Yang (2009) find that children in Indonesia that experienced higher rainfall are generally taller as adults. Similarly, Omiat and Shively (2020) find that children in Uganda who experience more rainfall generally have higher weight-for-height (less wasting). This literature is compelling because rainfall shocks are exogenous, so we can assume that the only way for rainfall to positively affect child health is through improved food security.

H1c: Households in treatment locations show better food security-related health outcomes.

2.2 Income

Poverty levels in Mali are as alarming as food security; Mali has one of the lowest per capita incomes in the world. Cattle herding used to be one of the main sources of food and income, but has largely collapsed in part as a result of the Sahel droughts of the 1970s and 1980s. Increasing the income of the target population is another key goal of the studied interventions. Assuming that the above-outlined impact chain unfolds, farmers should be in a position to sell excess produce. The same assumptions and risks related to increasing agricultural production as those discussed under food security apply. In order to generate income from an increased production, sufficient market infrastructure and market access need to be in place (AfDB, 2020).

H2: Households in treatment locations have a higher income than those in control locations.

Besides a number of assumptions that need to be met for the irrigation projects to contribute to household income, there are also several factors that put the intended impact at risk, one being prices for agricultural output that are too low to contribute to a substantial increase in farmers' income from selling their crops. In addition, past research has also identified potential unintended consequences of introducing irrigation that are related to poverty. Specifically, the intervention may increase poverty by making farmers shift to more capital-intensive production methods, potentially increasing their vulnerability in circumstances where future harvests are lost due to climate change (Lioubimtseva and Henebry, 2009). We will explore these potential effects empirically.

2.3 Gender equality

In the farming communities that are the target group of the studied interventions, households are oftentimes headed by women; their husbands may be absent due to work-migration, their involvement in the conflict (on the side of the military or the rebels) or because they died in the conflict. The husbands' absence means that women are increasingly responsible for their family's food security. At the same time, research indicates that female farmers often operate under worse conditions than their male counterparts, one reason being their lack of financial means. This makes it difficult for women farmers to purchase inputs (Perez et al., 2015), to hire labour, or to sponsor communal labour (Pender and Gebremedhin, 2006; Perez et al., 2015) and to gain access to labour-saving technology such as oxen (von Braun 1989). Female farmers have worse access to capital to take out loans and repay credit (Chipande, 1987).

Female farmers in Mali also on average hold less land than men, and female-owned land is of poorer quality and with a less secure tenure (Perez et al., 2015). The unfavourable conditions for female farmers certainly partly stem from the generally under-privileged position that women hold in Mali, in particular in rural communities structured according to a patriarchal hierarchy. This not only relates to female farmers being poorly endowed with agricultural inputs, labour and land, but also adversely impacts their access to knowledge.

These factors may limit female farmers' potential to intensify agricultural production and potentially also to adapt climate-smart agricultural practices whose introduction may require upfront investments that are difficult to make with limited financial means. This is why several GDC projects try to ameliorate the conditions for women living in the communities and for women farmers in particular. In many projects that rely on the intervention type of pump-based irrigation, a share of plots per so-called village perimeter is reserved for women farmers. Female farmers typically grow vegetables in Mali so that on the outcome level an increase in vegetable production in treatment locations should be observable. Assuming that these women farmers are successful in increasing their agricultural production through irrigation and that they generate income from the marketing of their crops, the share of these women's contribution to household income is supposed to increase. This target on the output-level is intended to lead to an increased influence of/respect for women on the impact level, which in turn is supposed to contribute to an increase in gender equality in the target communities.

H3a: Women's decision-making power is higher in treatment than in control locations.

H3b: The higher the share of women farmers per perimeter, the higher the decision-making power of women in the target communities.

2.4 Conflict

Mali has long struggled with armed conflict. Shortly after its independence, it experienced an uprising by the Tuareg population in 1963, followed by a coup d'état in 1963 and another Tuareg uprising in the early 1990s, before the turnover to democratic rule. However, democratic governments in the 1990s and 2000s were fragile, and the frustration about their mismanagement was one of the reasons – besides the fall of Gaddhafi's regime in Libya – for another Tuareg rebellion in 2012 (Bodian et al., 2020), which escalated on the declaration of the independent state of Asawad in northern Mali. Today's conflict has at least two main dimensions: a national political conflict and a violent conflict in the north of Mali, which are interlinked. The regions most affected by the violent conflict are the north and centre of Mali (see Buhaug and von Uexkull, 2021; Koubi, 2019; Mach et al., 2019).

The conflict may have a number of impacts on the interventions we study. First, GDP shrank significantly between 2010 and 2015, accompanied by a sharp rise in wasting and stunting among children (KfW, 2020), contributing to the discussed vulnerabilities related to food security and income of the target population.[6] Against this backdrop, the conflict corroborates the need to make farmers more resilient to future loss of harvests. Second, the armed conflict may limit the effectiveness of the intervention, either by directly interrupting project activities (e.g. attacks on infrastructure, intimidation or forced migration of farmers) or by increasing the risk of future losses, which may make farmers hesitant to invest in increasing agricultural productivity and in adopting new technologies.[7] Third, and most relevant for the present study, the projects under study aim to contribute to social and economic stabilisation. There are several pathways through which the intervention may impact conflict risk and intensity in treatment locations.[8] On the one hand, recent research suggests that between 3% and 20% of conflict risk over the past century has been influenced by climate variability or change (Froese and Schilling, 2019; Koubi, 2019; Mach et al., 2019). One plausible link between climate change and conflict is competition over increasingly scarce resources (Bagozzi et al., 2017; Koren and Bagozzi, 2017; Linke and Ruether, 2021). It is hence plausible that in Mali the competition for scarce resources may play an ever-important role in the multi-causal ongoing armed conflict, even if such relationship has not been confirmed for Mali in the past (Benjaminsen et al., 2012).

According to the projects' logframes, the interventions are supposed to either be neutral on conflict risk or decrease the risk of conflict. Besides the lowering of conflict risk through increasing the target groups' material wellbeing, some of the project components also aim to decrease conflict risk and intensity by contributing to better living conditions, as well as increasing interactions and dialogue

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[6] See Buhaug and van Uexkull (2021); Koubi (2019); Mach et al. (2019) on how armed conflict increases climate vulnerabilities in general.

[7] We address this by including different conflict measures as confounders in our statistical models of the effects of irrigation on food security, income and women empowerment.

[8] Of course, the intervention and its success are also impacted by conflict. In some cases, projects need to be situated in other places than initially planned, due to an ongoing conflict. In addition, conflict may disrupt the intervention, either because infrastructure gets destroyed through armed attacks (Kimenyi et al., 2014: 60) or farmers are intimidated by the violent conflict so that they cannot continue farming their fields; among many other ways in which the armed conflict may hamper the unfolding of the projects' potential positive impacts. The potential influence of the conflict on the project is addressed by adding conflict risk and/or intensity as a control variable in the statistical models.

between different ethnic groups and/or conflict parties through activities in advisory boards or user committees. However, there are also plausible ways in which the interventions may increase conflict risk. Anecdotal evidence from northern Mali suggests that conflicts between farmers often revolve around an owner of a field reclaiming it from the farmer to whom it was loaned (Beeler, 2006), over the shared use of fields (Benjaminsen et al., 2012), or the expansion of agriculture at the expense of livelihoods for pastoralists (Beeler 2006, 13). Accordingly, all groups of farmers that apply for an irrigation project in their village are required to facilitate a peace agreement of all stakeholders in the village, in order to avoid land conflicts. In addition to conflicts within treatment communities, the intervention could also spark conflict with neighbouring communities if irrigation activities at project sites negatively affect water availability elsewhere, for example.[9]

H4: Treatment locations have a lower conflict risk/intensity than control locations.[10]

2.5 Environmental conditions

Land conversion plays a crucial role in the functioning of ecosystem services. The majority of land changes globally (60%) are associated with human activities, and others (~40%) are due to climate change (Song et al., 2018). In Mali the ratio of such change may differ from the projected global land trends, but the drivers of change are the same. For example, steppe and savanna, two predominant land cover types in Mali, have experienced a substantial loss of area due to climate change and human activities. The decrease in the steppe grassland in the north is due to the expansion of sandy areas, a damaging outcome of change in precipitation patterns. Loss of savanna across southern Mali is due to the conversion of grassland to farmland (USGS, 2013). Therefore, any shift in the region’s climate patterns may threaten both food security and grassland ecosystems. Farmers have also shifted from reliance on rainfed agriculture to irrigation. For example, irrigated acreage increased by 400 percent between 2000 and 2015, mainly along the Niger River and in the southern part of the Inner Niger Delta, which is home to a highly dynamic and complex ecoregion that relies on seasonal flooding. Gallery forests (i.e., the forest along rivers and wetlands) decreased substantially (~23%) due to farming activities between 1975 and 2013. Loss of these forests and grassland have resulted in severe water erosion of the soil, loss of biodiversity, and declining land productivity (USGS, 2013). Therefore, any change in climate pattern and land conversion may severely affect the Inner Niger Delta and threaten both the region’s food security and the grassland ecosystem.

Projected climate change also has ramifications for the local ecosystem, with the potential of biodiversity loss (Bellard et al., 2012; Sala et al., 2000; Thomas et al., 2004) and impacts on pastoral livelihoods and ecosystem productivity (USAID, 2018). One of the consequences of climate change that is particularly relevant to the irrigation interventions being studied is land degradation (Olsson et al., 2019). Dry soil has a reduced capacity to absorb water (infiltration capacity). Therefore, extreme precipitation events after longer dry periods can cause fertile layers of soil to be washed away, exposing sandy layers that are more prone to erosion by wind. This land degradation may further lead to the loss of biodiversity (IPBES, 2018; UNCCD, 2019). Irrigation infrastructure may, in the long-term, minimise the ecological impacts of changes in hydrological regimes on ecosystems by improving soil moisture, reducing the risk of water erosion, and increasing crop diversity. Well-measured irrigation can increase soil moisture, improve groundwater levels and increase crop diversity. In addition to those potential benefits of irrigation itself, the interventions under study are accompanied by specific

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[9] See Duflo and Pande (2007) on how the effects of irrigation on rural poverty can be a paradox. The intervention may decrease water availability for other users, particularly downstream from project locations (and also for other sectors). This will be addressed in the statistical models.

[10] We follow the logframes and formulate a conflict-reducing expectation, although the effects might well be in the opposite direction, which is an empirical question.

erosion-protection measures, such as the creation of stone contour walls and the planting of trees, hedges, and vegetation cover.

The project's logical framework assumes that irrigation is carried out efficiently and within an optimal intensity, as both insufficient and excessive irrigation are environmentally destructive. Typically, insufficient irrigation hampers positive effects on soil moisture and crop diversity. Excessive irrigation, particularly if coupled with excessive use of fertilizer, may lead to salinization of soil and groundwater (Olsson et al., 2019). Besides excessive irrigation, there are other potential unintended negative consequences of the interventions. Farmers may construct field fences from surrounding trees to protect their irrigated fields from cattle, resulting in an overuse of the natural shrub and tree vegetation in the catchment area of the irrigation fields. Also, increased grazing activity around small dams due to the access to drinking water for cattle may jeopardise the positive effects of irrigation on the ecology. The interventions under study are accompanied by knowledge transfer programmes. According to the projects' theories of change, the communities that benefit from the projects are assumed to use resources responsibly and sustainably so that those unintended impacts on the fauna should be avoided. KfW project evaluations suggest no significant negative ecological impacts attributable to the interventions (KfW, 2011).

Excessive irrigation, and often abandonment of farmland due to lack of water, both cause soil erosion that affects land productivity and requires more effort to improve crop yield. Irrigation interventions are therefore expected to maintain water availability to farming practices, retain organic matter in topsoil and thereby minimise soil erosion and improve crop yields.

H5a: Treatment locations have a lower risk of erosion than control locations.

The type of irrigation system (e.g. valorisation or pump, etc.) tends to affect the availability of soil moisture and groundwater table. The valorisation process increases soil moisture that permeates the soil and later replenishes the water table. Thus, valorisation compensates for the effects of harvesting groundwater using a pump-based irrigation system. Therefore, irrigation interventions, independent of the region's precipitation, may improve soil moisture. However, whether the increased soil moisture helps to improve crop yield entirely depends on soil substrate and how far the projects sites are from the river system, since excess water contributes to surface runoff and evaporates in summer.

H5b: Treatment locations have higher soil moisture than control locations.

Availability of irrigation water typically increases the cropping intensity (i.e. number of harvests per year), which aids crop diversity. However, it depends on the soil type and fertility, and the frequency of flood events in the region. Irrigation interventions around the Niger River may offer farmers higher crop yields and diversity due to the Niger River's fertile soil.

H5c: Among cultivated land, crop diversity is higher in treatment than in control locations.

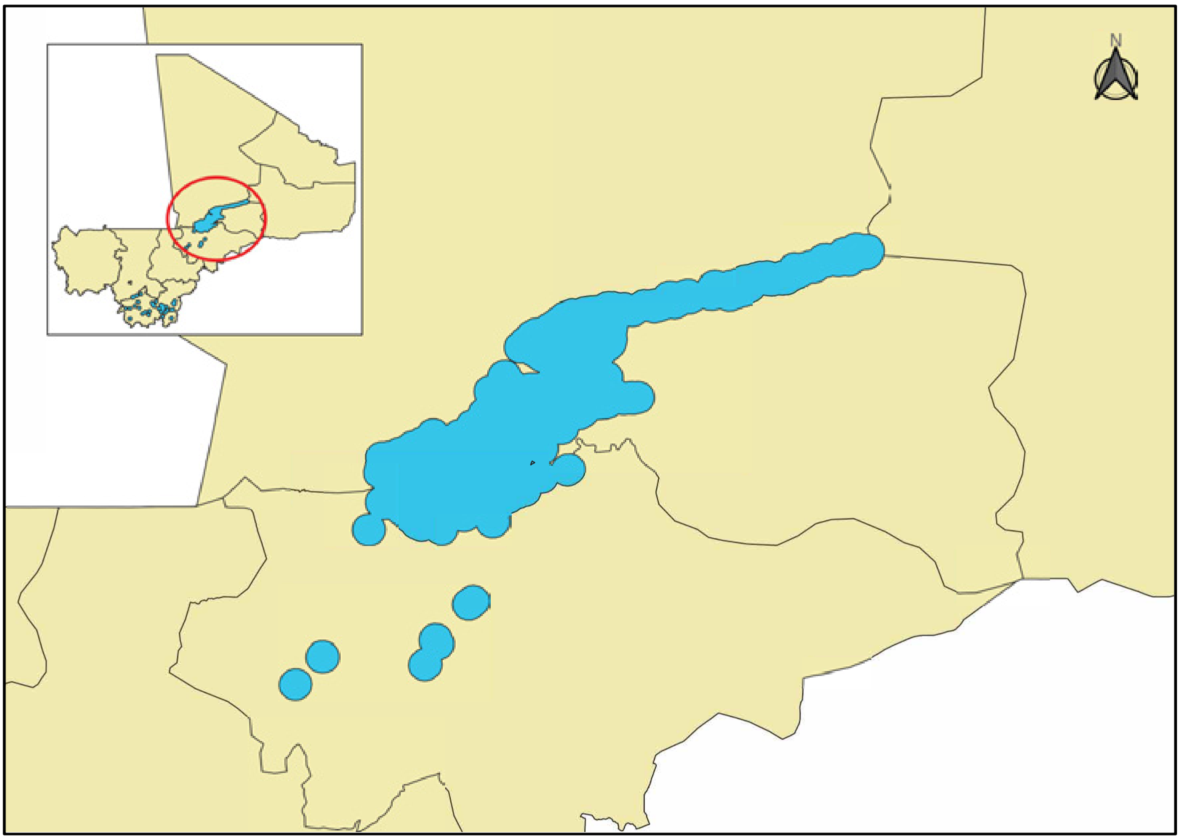
3. EMPIRICAL STRATEGY

3.1 Data

Project sites: Mali Nord/IPRODI

The Mali Nord/IPRODI project sites in northern Mali represent over 20 years of irrigation intervention activities in Mali's Inner Niger Delta region (Figure 2). The collection of activities from 1999 to 2020 consist of several different initiatives and umbrella projects by the German government and its partners. These include Mali Nord (pre 2010), PAIP (Projet d'appui à l'irrigation de proximité – Local Irrigation Support Project) 2010–2014; IPRODI (Irrigation Projects – Inner Delta) since 2015, and merged with REAGIR II (Renforcement de l'agriculture irriguée) in 2018; and IPRO-REAGIR I/II/III, Component Inner Delta, since 2010. Due to the number of top-level projects, often overlapping, this paper will broadly refer to this collection of projects as "Mali Nord" and explicitly state any instance where a specific project (e.g. Mali Nord vs. IPRO-DI) is being used in the analysis or otherwise referenced.

Figure 2 Mali Nord project area



Source: authors' own figure

Note: This area is based on a dissolved 10 km buffer of all project sites in Mali Nord.

In total, there are 942 project sites in Mali Nord. Of these, 792 are classified as pump-based irrigation (rice-growing plots (PIV) or market gardens (PIM)) and 150 are flooded areas, or *mares*. Northern Mali has a broader availability of GIS data for project sites compared to other regions due to the amount of conflict in the region. While project sites in other regions can typically be visited and monitored in person, conflict in the north has necessitated the use of remote monitoring using GIS data (see Figure A1.1 in Annex 1 on project polygons in the Mali Nord project area).

Project sites: IRRIGAR Sikasso

The Sikasso project sites represent a subset of the IRRIGAR (Initiative de Renforcement de la Résilience par l'Irrigation et la Gestion Appropriée des Ressources[11]) projects in the Sikasso region. IRRIGAR is a continuation of the earlier programmes IPRO-DB (irrigation projects in Dogon and Bélédougou areas[12]) and IPRO-SI (irrigation projects in Sikasso region). IRRIGAR was implemented by the AHT Group over two phases. Phase I[13] took place from 2014 to 2017 and Phase II[14] continued from the end of Phase I in 2017 to 2019. Both phases were funded by BMZ, the European Union and the United States Agency for International Development (USAID), through the KfW.

The original data on these project sites were collected as part of a limited exploratory effort to test methods for documenting project site locations using satellite imagery. As a result, similar data were not available for interventions in other regions of the IRRIGAR projects (i.e. Koulikoro). Data were provided in the form of PDF files containing imagery of the project site, with project boundaries overlain (for an example see Figure A1.2 in Annex 1). Project boundaries were delineated within each map to identify various project components, including dykes, flooded areas, rice cultivation and market gardens. Exact dates for construction or other stages of individual project sites were not available.

Because standard PDF images are not geospatially referenced, or compatible with other geospatial datasets for analysis, it was necessary to georeference the PDF images and trace the project boundaries. The project PDF files were first georeferenced using the geographic information system application QGIS. Common points in both the PDF image and satellite imagery from Google Maps were identified so that the PDF image could be assigned a geographic coordinate reference system to support further geospatial analysis. Once the images were georeferenced, the project boundaries were manually traced using QGIS. Each individual project feature was traced and the associated project and feature type (e.g. flooded area/mare) was recorded (see Figure 3).

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[11] https://www.dngr.gouv.ml/projets-programmes/pnip/ipro-irrigar/

[12] Dogon country (Bandiagara) and the Koulikoro region (Bélédougou)

[13] https://www.aht-group.com/cms/projects/africa/mali/small-scale-irrigation-initiative-to-reinforce-resilience-through-irrigation-and-the-appropriate-management-of-resources-irrigar

[14] https://www.aht-group.com/cms/projects/africa/mali/small-scale-irrigation-initiative-to-support-resilience-through-irrigation-and-the-appropriate-management-of-resources-ipro-irrigar

Figure 3 Locations of polygons resulting from georeferencing PDFs and tracing features

Source: authors' own figure

Note: The map provides an overview of the georeferenced project site locations in Sikasso.

From the 36 IRRIGAR I/II project sites in Sikasso, a total of 576 features were defined. Project sites were identified as IRRIGAR I or IRRIGAR II by cross-referencing lists of the communes that were part of each IRRIGAR phase, and verified using yearly crop production tables for each commune. Establishing the IRRIGAR phase of project sites provides a temporal frame of reference to be used during analysis.

Remote sensing of agricultural production

To develop measures of agricultural production for the study area, we used Google Earth Engine (GEE) and a built-in data catalogue. GEE offers global time-series, multi-resolution satellite imagery, cloud-based computing and, in particular, access to algorithms for users. One of the advantageous aspects of using GEE is its ability to conduct parallel analysis that speeds up the automation process considerably compared to desktop computing. Our efforts were focused on developing measures of agricultural production using satellite imagery, such as Landsat series imagery (e.g. Landsat 5, 7 and 8). Vegetation and water indices indicative of agricultural production were developed from the Landsat series of imagery. Examples include NDDI (normalised difference drought index), NDVI (normalised difference vegetation index), and NDWI (normalised difference water index).

Landsat satellites provide high-quality, multi-spectral imagery that reaches back to 1972. Landsat series imagery provides global coverage on a regular basis. Imagery from Landsat sensors is available for free and comes with high spectral resolution. The spatial resolution of these images (i.e. Landsat 5, 7 and 8) is 30 metres and carries multiple bands both in the visible and infrared portion of the electromagnetic spectrum. We used bands from both portions. For example, red and near-infrared (NIR) bands were used to calculate NDVI, and NIR and short-wave infrared (SWIR) bands were used to calculate NDWI.

Shapefiles of project clusters (i.e. polygon) from Mali north and Sikasso regions were imported to the GEE environment to estimate water (e.g. NDDI and NDWI) and vegetation (e.g. NDVI) indices from 1986 to 2021 for capturing impacts of before and after irrigation interventions efforts. We analysed images from Landsat 5, 7 and 8 sensors by setting the limit of cloud cover to less than 10%. During the pre-processing steps, we calibrated imagery from these sensors to develop normalised vegetation and water indices. The NDDI index is suitable for measuring the dryness of a particular area. It is calculated using bands from red, NIR, and SWIR electromagnetic spectrum. Likewise, NDWI, which uses bands from the NIR and SWIR portions of the spectrum, is suitable for measuring plant water content and works as a very good proxy for plant water stress. We also developed NDVI, which describes the difference between visible and near-infrared reflectance of vegetation cover.

We extracted values of water and vegetation indices for each project site in CSV (comma-separated values) format that included minimum, maximum, average and standard deviation statistical measures for each year from 1986 to 2021. In the final step, we joined each project value with the database for statistical analysis.

Demographic and Health Survey

The Demographic and Health Survey (DHS) is a multinational cross-sectional household survey funded by USAID. The survey focuses on population, health and nutrition, and is conducted approximately every five years in its target countries. The DHS has been conducted in Mali over six waves, and GPS coordinates of survey locations were collected for the five most recent waves. We utilise the five survey waves with GPS coordinates: 1995–96, 2001, 2006, 2012–13, and 2018. The DHS includes a household survey, a men's survey and a women's survey. As part of the women's survey, information is also collected on female respondents' children (see Figure A1.3 in Annex 1 for survey locations).

We use a number of measures collected from the DHS in our analysis of child nutrition and health, employment and income, and women's empowerment. Our analysis of child nutrition includes a measure of child mortality from the birth record collected in the women's survey. In addition, we use reported measures of low birth weight and childhood illness, as well as biomarker measures of child stunting, wasting and body mass from the child record collected in the women's survey.

Our measures of employment include a measure of current and agricultural employment from the men's and women's surveys. Our measures of income include asset levels collected in the household survey.

Our measures of women's empowerment include measures constructed from a number of decision-making questions asked in the women's survey. In addition, we use measures constructed from questions regarding opinions on intimate partner violence (IPV) that are asked in the women's survey

As the last wave of the DHS in Mali occurred in 2018, prior to completion of Sikasso projects, our analysis using DHS outcomes is limited to IPRODI/Mali Nord project sites. We therefore limit our DHS samples to households and individuals who live within 6 km of IPRODI/Mali Nord project sites. It is important to note that, due to the March 2012 coup d'état, the 2012–13 DHS round does not include the regions Kidal, Timbuktu and Gao, or three circles in Mopti which are surveyed in other rounds. As IPRODI/Mali Nord project sites are across Timbuktu and Mopti, we do not observe any areas near project sites in Timbuktu and some of the areas near project sites in Mopti for the 2012–13 round.

The distribution of clusters in our sample (i.e. clusters within 6 km of IPRODI/Mali Nord project sites) is presented in Figure A1.3. There is significant geographic and temporal variation in the distribution of DHS clusters among IPRODI/Mali Nord project sites.

Living Standards and Measurement Survey

The Living Standards and Measurement Survey (LSMS) is a household survey project organised by the Survey Unit of the World Bank's Development Data Group, in cooperation with national statistical offices around the world. The Enquête Agricole de Conjoncture Intégrée aux Conditions de Vie des Ménages (EAC-I) is a panel survey within the LSMS programme that focuses on household-level agricultural statistics in Mali. Each wave of the EAC-I is administered in two visits. Enumerators visit the same household post-planting and post-harvest. Both the 2014 and 2017 EAC-I waves are used in this impact evaluation. They include 3 804 households and 3 813 households, respectively. While 953 of the enumerated areas are visited in both 2014 and 2017, different households are visited between waves within each area, therefore the study is still cross-sectional.

We use multiple indicators from the LSMS to analyse household-level income, food security, and agricultural consumption and production. Total income is measured as agricultural income plus non-agricultural sources of household income. Food security is measured by the household head's responses to questions on hunger and food variation. Agricultural production and consumption are measured as kilograms of all crops produced and then consumed by the household in the survey year. Crop sale value is also used to quantify the impact of completed projects on agricultural quality changes (see Figure A1.4 in Annex 1 on LSMS survey locations).

Ancestral characteristics

We used the *Ethnographic Atlas* (Murdock, 1967) to assess impacts of project completion on ethnic groups with variant levels of pastoralism and matrilineality. The *Ethnographic Atlas* is a database of 1 265 ethnic groups, 239 of which are in Africa, assembled by Murdock between 1962 and 1980. The database contains 114 variables on each ethnic group, from settlement patterns to pottery-making habits. We identified 11 ethnic groups from the DHS survey, and used *Ethnographic Atlas* variables on their levels of pastoralism and matrilineality.

A pastoral variable is generated for each ethnic group in the DHS by replicating McGuirk and Nunn (2021), whose pastoral variable was originally developed by Becker (2019). The pastoral variable combines information on the percentage of animal husbandry in which the ethnic group participates (on a 0–1 scale, v4 in the *Ethnographic Atlas*) and a binary indicator variable for whether or not the ethnic group's most important large animal can be herded (v40). Matrilineality was also assessed, using variables on land inheritance (v74), movable property inheritance (v76), and descent line (v43).

Conflict

To assess conflict around German-funded irrigation project sites in the Mali Nord and Sikasso regions of Mali, this evaluation used the ACLED (Armed Conflict Location & Event Data Project) dataset. ACLED was selected from several existing conflict datasets (SCAD, UCDP-GED, etc.) based on its broad spatial and temporal coverage, and the amount of event data available. See Annex 1 for a comparison of ACLED with other conflict datasets.

ACLED includes a broad range of event types, such as battles, violence against civilians, explosions, riots and protests, which can be further refined based on actors involved (state forces, rebels, civilians, etc.), type of interactions (i.e. pairing of actors involved) and fatalities. For the purposes of this evaluation, the data were refined into six groups of actors. These include state actors (e.g. police or military forces of Mali), external actors (e.g. foreign militaries), jihadist groups, militias, other named organisations and all others (e.g. civilians, rioters). See Annex 1 for a detailed description of the filters used for these groups.

The data from ACLED contain nearly 5 000 events between 1997 and the present, with fewer than 30 events prior to 2000, and approximately 70 between 2000 and 2010. Given that the Mali War began in 2012, the lack of earlier conflict data may be in line with actual trends, yet may be impacted due to gaps in historical coverage (see Figure A1.5 and Figure A1.6 in Annex 1 for ACLED locations).[15]

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[15] All conflict datasets evaluated had similar temporal trends for event coverage.

Environmental conditions

We used very high-resolution (VHR) and high-resolution (HR) satellite imagery to assess ecological impacts. Due to high temporal resolution, PlanetScope (visual assets quality – monthly mosaics) was selected for HR imagery that offered seasonal changes (i.e. within a year). PlanetScope is a constellation of more than 125 satellites. It maps the entire land surface of the Earth at a very high temporal resolution. Visual assets are orthorectified, colour corrected, RGB imagery products. These products are optimised for the human eye for simple and direct visual inspection. The spatial resolution of imagery from the PlanetScope constellation is 3 and 5 metres per pixel. In this study, PlanetScope images at 3 metres were utilised for quantifying ecological impacts due to irrigation infrastructure for each year from 2016 and 2021 through visual interpretation.

VHR images from several optical sensors were also analysed through visual interpretation to capture ecological impacts before, during and after irrigation implementation. The spatial resolution of VHR images ranged from 0.3 metres (i.e. WorldView-3/4: 0.3-m; GeoEye-1: 0.4 cm; Pleiades: 0.5 m, etc.) to 1 metre (i.e. KOMPSAT-2: 1 m) (see Table A1.1 in Annex 1 for an overview). The VHR imagery offers ample opportunities to monitor complex land ecosystems for ecological impacts. VHR optical sensors provide multispectral (MS) and panchromatic (PAN) imagery at much finer spatial resolutions (at sub-metre spatial resolution) compared to freely available moderate-resolution imagery (e.g. Landsat and Sentinel, etc.). The IKONOS satellite, launched on 24 September 1999, was the first commercial high-resolution satellite sensor that provided imagery at 1-metre spatial resolution (i.e. panchromatic band and pan-sharpened multispectral at 1 m). Currently, there are several satellite sensors (e.g. WorldView, QuickBirdand GeoEye) that offer VHR imagery.

3.2 Methodology

Our analysis relies on a combination of difference-in-difference (DID) analysis with fixed effects and visual interpretation of VHR imagery. We utilise DID on both panel and repeated cross-sectional data, depending on the structure of the data in question. In both cases, our treatment and comparison groups consist of the areas themselves or the individuals residing in the areas surrounding project sites. The control group consists of observations of these areas at points in time prior to the project being completed, and the treatment group consists of observations of these areas at points in time after the project has been completed.

The DID approach allows us to estimate a treatment effect by calculating the difference between the control and treatment groups in the change over time in our various outcomes of interest. A key assumption of the DID approach is that the control and treatment groups' time trends would be parallel in the absence of treatment. As both our control and treatment groups consist of actual project locations, it is likely that the groups are sufficiently similar to fulfil this assumption. The main threat to this assumption would be if project sites that were completed earlier were prioritized due to diverging time trends. We minimise this risk by using a rich set of geographic and temporal fixed effects that control for geographic- and time-invariant characteristics that may influence the relevant outcomes of interest. For a subset of our outcomes, event study designs are feasible, and we find no evidence of diverging pre-trends associated with treatment timing.

This DID approach provides more reliable causal estimates than do other potential approaches, since it allows us to construct a plausible counterfactual of what would have occurred at project sites in the absence of treatment based on changes occurring in locations that had yet to be treated (but would eventually be). For instance, an alternative method of assessing the impact of the irrigation projects would have been to take project sites as our treatment group and find similar locations in Mali, using propensity score matching, that never received a project nearby to make up our control group. However, even if we had found close matches to our treatment group in terms of a number of geographic, economic, and demographic characteristics, there would still remain the question of why the treatment group was selected for projects and the matched sites were not. Due to this unexplained process of selection, the counterfactual in this scenario would not be as compelling and the treatment effect not as robust. By using only those areas that received projects in our sample, we are able to ensure that the treatment and control groups are sufficiently comparable to produce a treatment effect that can be interpreted causally.

Agricultural production

To estimate the effect of project completion on agricultural production, we use a panel dataset at the polygon-year unit of analysis. Each polygon is first irrigated in a specific year, and this timing varies across all the polygons in our sample. We use this variation in timing of irrigation completion to draw comparisons between those observations in which the polygon is already irrigated and those that are not yet irrigated. In other words, each polygon is part of both the treatment and comparison groups, depending on whether the year of the observation is before or after that specific polygon's irrigation completion. We use a DID methodology to do so, estimated via two-way fixed effects that adjust for the unobserved factors specific to each polygon and common shocks happening in each region and year. In order to understand the time-path of treatment effects, we use time-to-treatment bins in this estimation.

Our primary estimating equation for agricultural production outcomes is the following:

$$\boldsymbol{AgOutcome_{irt} = \alpha + \textstyle\sum_{y=-10}^{10+} \beta_y \, YearToTreatment_{irt} + \gamma Precip_{irt} + \lambda Temp_{irt} + D_i + D_{rt} + \epsilon_{irt}}$$

where $AgOutcome_{irt}$ is the outcome (discussed below) in polygon *i* in region *r* in year *t*, $\sum_{y=-10}^{10+} \beta_y \, YearToTreatment_{irt}$ represents a set of coefficients and dummies indicating year-to-treatment bins, $Precip_{irt}$ and $Temp_{irt}$ are the total precipitation and mean temperature in the polygon-year, and $D_i + D_{rt}$ are a set of fixed effects for polygon and region-year.

As the relevant outcome measures, we examine both the availability of water on the polygons and vegetation greenness. We use the NDWI prior to the rainy season to capture the possible extension of the growing season via irrigation. We also use the NDVI in both the pre-rainy season and the rainy (or typical growing) season to reflect the potential impacts of irrigation on actual crop production.

We estimate all models via ordinary least squares (OLS), with standard errors multi-way clustered by region and year.

Child nutrition and health

To determine the impact of project completion on child nutrition and health, we utilise a cross-sectional dataset that includes children of female DHS respondents who were surveyed in any of the five most recent waves and live within 6 km of a project site. This dataset includes information on project completion, as well as measures of child nutrition and health from the DHS. We group children into three distance bands from the nearest project site: 0–2 km, 2–4 km and 4–6 km. As the DHS survey is cross-sectional, each individual is observed only once. Some individuals are observed before the nearest project to them is completed and some are observed after the nearest project is completed. As such, the dataset includes both a treatment and a control group. The treatment group consists of individuals who live within 6 km of their nearest project site and are observed after that project is completed, while the control group consists of individuals who live within 6 km of their nearest project site and are observed before that project is completed.

Given these treatment and control groups, we implement a DID strategy to calculate the treatment effect on a number of measures of child nutrition and health in each of the three distance bands, including child mortality, low birth weight, child stunting, child wasting, child body mass, and childhood illness. The DID allows us to estimate a treatment effect by calculating the difference between the treatment and control groups in the change over time in child nutrition and health. In other words, our control group demonstrates the counterfactual of how child nutrition and health would have changed over time if treatment never occurred. Observing our treatment group allows us to see how child nutrition and health changed over time when treatment did occur. As such, the difference in the time trends between the treatment and the control group reveals how child nutrition and health changed as a direct result of treatment.

Depending on the outcome, we consider treatment either before birth (i.e. a child is considered to be treated if the nearest project site was completed prior to the child's birth), before survey (i.e. a child is considered to be treated if the nearest project site was completed prior to the DHS survey date), or before age 5 (i.e. a child is considered to be treated if the nearest project site was completed prior to the child's fifth birthday). In the case of child mortality, only treatment before age 5 is considered, as child mortality is defined as mortality before age 5, and any investment in the project site before that age may impact the outcome. In the case of low birth weight, only treatment before birth is considered, as investment after birth is irrelevant to the outcome. In the case of recent child illness (including current anaemia, recent diarrhoea, and recent fever or cough), only treatment before survey is considered, as the most recent investments are most relevant to the outcome. Finally, in the case of child stunting, wasting, and body mass, both treatment before birth and treatment before survey are considered, as both prenatal and childhood investments are likely to impact the outcome.

To ensure proper estimation of the treatment effect on child health and nutrition, we utilise region fixed effects to control for time-invariant local characteristics, time fixed effects (wave fixed effects when considering treatment before survey and birth cohort fixed effects when considering treatment before birth or treatment before age 5) to control for geographic-invariant characteristics within each temporal grouping, and distance-band fixed effects to control for time- and geographic-invariant characteristics within each distance band. This allows us to estimate the counterfactual outcomes of treated locations based on each location's local average outcome and variations that are common across all locations in each wave or birth cohort.

Our primary estimating equation for child health and nutrition outcomes is the following when considering treatment before survey:

$$y_{idrt} = \alpha + \beta_d TreatBand_{idrt} + D_d + D_r + D_t + \varepsilon_{idrt}$$

where y_{idrt} is the child nutrition or health outcome of interest for child i in distance-band d from the nearest project site in region r and survey year t, $TreatBand_{idrt}$ is a dummy variable indicating whether child *i* in region *r* was treated before survey year *t* broken down into distance bands *d* from the nearest project site (0–2, 2–4, and 4–6 km), D_d reflect distance-band fixed effects, D_r reflect region fixed effects, and D_t reflect wave fixed effects. No additional control variables beyond these fixed effects are included in the specification.

Our primary estimating equation for child health and nutrition outcomes is the following, when considering treatment before birth:

$$y_{idrb} = \alpha + \beta_d TreatBand_{idrb} + D_d + D_r + D_b + \varepsilon_{idrb}$$

where y_{idrc} is the child nutrition or health outcome of interest for child *i* in distance-band *d* from the nearest project site in region *r* and born in year *b*, $TreatBand_{idrb}$ is a dummy variable indicating whether child *i* in region *r* was treated before birth year *b* broken down into distance bands *d* from the nearest project site (0–2, 2–4, and 4–6 km), D_d reflect distance-band fixed effects, D_r reflect region fixed effects, and D_b reflect birth cohort fixed effects. No additional control variables beyond these fixed effects are included in the specification.

As we do not have DHS data on child nutrition and health for any years after Sikasso projects were completed, we do not have sufficient data to calculate a treatment effect of Sikasso projects. Therefore, our child nutrition and health analysis is limited to children within 6 km of a IPRODI/Mali Nord project site, and the treatment effect should be interpreted as the effect of IPRODI/Mali Nord treatments.

Economic well-being

To determine the impact of project completion on economic well-being, we utilise three cross-sectional datasets. The first dataset includes male and female DHS respondents who were surveyed in any of the five most recent waves and live within 6 km of a project site. This dataset includes information on project completion, as well as measures of employment from the DHS. The second dataset includes households from the DHS who were surveyed in any of the five most recent waves and live within 6 km of a project site. This dataset includes information on project completion, as well as measures of household assets from the DHS. The third dataset includes households from the LSMS who were surveyed in either wave of the EAC-I and live within 6 km of a project site. This dataset includes information on project completion, as well as income, food security and agricultural indicators. In each dataset, respondents are grouped into three distance bands from the nearest project site: 0–2 km, 2–4 km, and 4–6 km.

As both the DHS and LSMS surveys are cross-sectional, each individual or household in these datasets is observed only once. Some are observed before the nearest project to them is completed and some are observed after the nearest project is completed. As such, the dataset includes both a treatment and a control group. The treatment group consists of individuals or households who live within 6 km of their nearest project site and are observed after that project is completed, while the control group consists of individuals or households who live within 6 km of their nearest project site and are observed before that project is completed.

Given these treatment and control groups, we implement a DID strategy to calculate the treatment effect on a number of measures of economic well-being in each of the three distance bands, including employment, asset ownership, agricultural and total household income, crop sale value, agricultural consumption, production and food security. The DID allows us to estimate a treatment effect by calculating the difference between the treatment and control groups in the change over time in these measures of economic wellbeing. In other words, our control group demonstrates the counterfactual of how economic well-being would have changed over time if treatment had never occurred. Observing our treatment group allows us to see how economic well-being changed over time when treatment did occur. As such, the difference in the time trends between the treatment and the control group reveal how economic well-being changed as a direct result of treatment.

To ensure proper estimation of the treatment effect on economic well-being, we utilise local geographic fixed effects (region or circle) to control for time-invariant local characteristics, wave fixed effects to control for geographic-invariant characteristics within each wave, and distance-band fixed effects to control for time- and geographic-invariant characteristics within each distance band. This allows us to estimate the counterfactual outcomes of treated locations based on each location's local average outcome and variations that are common across all locations in each wave.

Our primary estimating equation for economic well-being measures from the DHS is the following:

$$y_{idrt} = \alpha + \beta_d TreatBand_{idrt} + D_d + D_r + D_t + \varepsilon_{idrt}$$

where y_{idrt} is the outcome of interest for individual or household *i* in distance-band *d* from the nearest project site in region *r* and survey year *t*, $TreatBand_{idrt}$ is a dummy variable indicating whether individual or household *i* in region *r* was treated before survey year *t* broken down into distance bands *d* from the nearest project site (0–2, 2–4, and 4–6 km), D_d reflect distance-band fixed effects, D_r reflect region fixed effects, and D_t reflect wave fixed effects. No additional control variables beyond these fixed effects are included in the specification.

Our primary estimating equation for economic well-being measures from the LSMS is the following:

$$y_{idct} = \alpha + \beta_d TreatBand_{idct} + D_d + D_c + D_t + \varepsilon_{idct}$$

where y_{idct} is the outcome of interest for household *i* in distance-band *d* from the nearest project site in survey circle *c* and survey year *t, $TreatBand_{idct}$* is a dummy variable indicating whether household *i* in survey circle *c* was treated before survey year *t* broken down into distance bands *d* from the nearest project site (0–2, 2–4, 4–6 km), D_d reflect distance-band fixed effects, D_c reflect survey circle fixed effects, and D_t reflect wave fixed effects. No additional control variables beyond these fixed effects are included in the specification.

As we do not have DHS or LSMS data for any years after Sikasso projects were completed, we do not have sufficient data to calculate a treatment effect on economic well-being of Sikasso projects. Therefore, our economic well-being analysis is limited to individuals and households within 6 km of an IPRODI/Mali Nord project site. The treatment effect should be interpreted as the effect of IPRODI/Mali Nord treatments.

Gender equality

To determine the impact of project completion on women's empowerment, we utilise a cross-sectional dataset that includes female DHS respondents that were surveyed in any of the five most recent waves and live within 6 km of a project site. This dataset includes information on project completion, as well as measures of women's decision-making power and opinions on the acceptability of IPV from the DHS. We group women into three distance bands from the nearest project site: 0–2 km, 2–4 km, and 4–6 km. As the DHS survey is cross-sectional, each individual is observed only once. Some individuals are observed before the nearest project to them is completed and some are observed after the nearest project is completed. As such, the dataset includes both a treatment and a control group. The treatment group consists of women who live within 6 km of their nearest project site and are observed after that project is completed, while the control group consists of women who live within 6 km of their nearest project site and are observed before that project is completed.

Given these treatment and control groups, we implement a DID strategy to calculate the treatment effect on a number of measures of female empowerment in each of the three distance bands, including women's self-reported decision-making power in various scenarios and their opinions about the acceptability of IPV in various scenarios. The DID allows us to estimate a treatment effect by calculating the difference between the treatment and control groups in the change over time in these measures. In other words, our control group demonstrates the counterfactual of how female empowerment would have changed over time if treatment never occurred. Observing our treatment group allows us to see how female empowerment changed over time when treatment did occur. As such, the difference in the time trends between the treatment and the control group reveals how female empowerment changed as a direct result of treatment.

In addition to variables that measure women's decision-making power and opinion of IPV in specific scenarios, we also utilise summary indices that aggregate these measures across all scenarios to represent an aggregate measure of decision-making power within the household and opinion of IPV. These indices are weighted to maximise the amount of information captured (based on the covariance matrix) and are used for two reasons (Anderson, 2008). First, use of the indices is robust to over-testing, as multiple outcomes are combined into one variable. Second, use of the indices is potentially more powerful than using individual level outcomes, as multiple outcomes with only marginal significance may be aggregated into a summary index that does attain significance.

To ensure proper estimation of the treatment effect on women's empowerment, we use region fixed effects to control for time-invariant local characteristics, wave fixed effects to control for geographic-invariant characteristics within each wave, and distance-band fixed effects to control for time- and geographic-invariant characteristics within each distance band. This allows us to estimate the counterfactual outcomes of treated locations based on each location's local average outcome and variations that are common across all locations in each wave.

Our primary estimating equation for economic well-being measures from the DHS is the following:

$$y_{idrt} = \alpha + \beta_d TreatBand_{idrt} + D_d + D_r + D_t + \varepsilon_{idrt}$$

where y_{idrt} is the outcome of interest (either individual or index) for woman i in distance-band d from the nearest project site in region r and survey year t, $TreatBand_{idrt}$ is a dummy variable indicating whether woman i in region r was treated before survey year t broken down into distance bands d from the nearest project site (0–2, 2–4, and 4–6 km), D_d reflect distance-band fixed effects, D_r reflect region fixed effects, and D_t reflect wave fixed effects. No additional control variables beyond these fixed effects are included in the specification.

As we do not have DHS data on women's empowerment for any years after Sikasso projects were completed, we do not have sufficient data to calculate a treatment effect of Sikasso projects. Therefore, our women's empowerment analysis is limited to women within 6 km of an IPRODI/Mali Nord project site. The treatment effect should be interpreted as the effect of IPRODI/Mali Nord treatments.

Conflict

To determine the impact of project completion on conflict levels, we utilise a panel dataset that includes all project locations across the years 1997–2021. This dataset includes information on project completion, as well as ACLED conflict counts within three distance bands surrounding project locations: 0–1 km, 1–5 km, and 5–10 km. The unit of observation within this dataset is at the project-by-year-by-distance level, and each project location is observed every year, both before and after project completion. As such, the panel dataset includes both a treatment and a control group. The treatment group consists of project locations that are observed after the project is completed, while the control group consists of project locations that are observed before the project is completed. Therefore, each project location is part of both the control and treatment group, depending on the year of observation.

Given these treatment and control groups, we implement a DID strategy to calculate the treatment effect on conflict in each of the three distance bands. The DID allows us to estimate a treatment effect by calculating the difference between the treatment and control groups in the change over time in conflict. In other words, our control group demonstrates the counterfactual of how conflict would have changed over time if treatment never occurred. Observing our treatment group allows us to see how conflict changed over time when treatment did occur. As such, the difference in the time trends between the treatment and the control group reveal how conflict changed as a direct result of treatment.

To ensure proper estimation of the treatment effect on conflict, we utilise both project-by-distance band fixed effects to control for time-invariant local characteristics and circle-by-year fixed effects to control for geographic-invariant characteristics within each circle-year combination. This allows us to estimate the counterfactual outcomes of treated locations based on each location's local average outcome and variations that are common across all locations in each circle and year.

Our primary estimating equation for conflict is the following:

$$\boldsymbol{Conflict_{idct} = \alpha + \beta_d TreatBand_{idct} + D_{id} + D_{ct} + \varepsilon_{idct}}$$

where $Conflict_{idct}$ is the count of conflict events in distance-band d surrounding project site i in circle c and year t, $TreatBand_{idct}$ is a dummy variable indicating whether project i in circle c was treated in year t broken down into distance bands d from the project site (0–1, 1–5, and 5–10 km), D_{id} reflect project-by-distance fixed effects, and D_{ct} reflect circle-by-year fixed effects. No additional control variables beyond these fixed effects are included in the specification.

We estimate the treatment effect on conflict in two ways. First, we estimate the effect on all conflict events reported in ACLED. Second, we estimate the effect on conflict events which do not involve state actors.

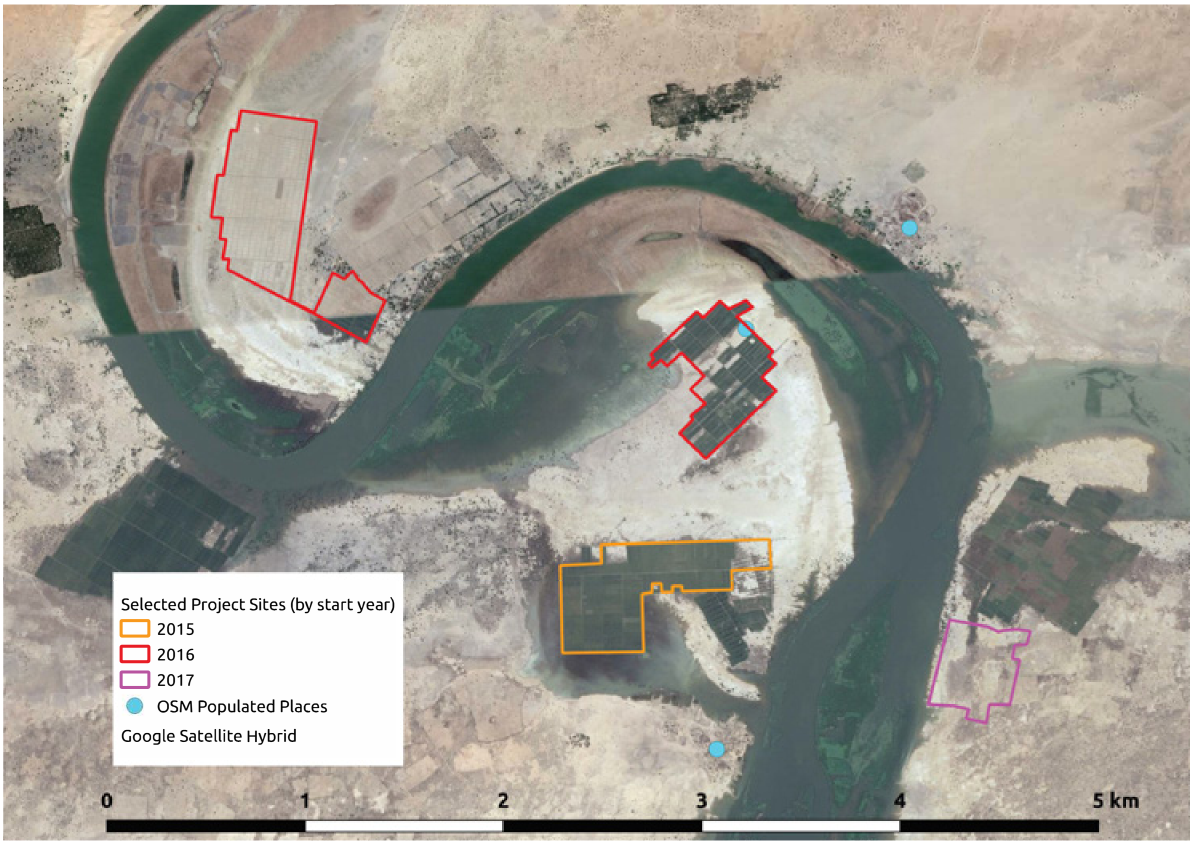
Environmental conditions

Irrigation infrastructure facilitates land conversions, leading to expansion of farmland and, subsequently, a wide variety of ecological impacts (i.e. soil erosion, soil moisture/groundwater, development, and crop diversity). This phenomenon is evident in Mali through the analysis of VHR (e.g. QuickBird: 0.65 m; WorldView-1/2/3: 0.46 m, etc.) and high-resolution (HR; PlanetScope: 3m) satellite imagery through the visual interpretation method. Landscapes that were classified as grassland, bare earth, or shrubs have been converted into farmland and cultivated extensively over time due to the establishment of irrigation infrastructure.

A total of 33 project sites across eight clusters (see Figure A1.7 in Annex 1) were selected for analysis of ecological impacts using VHR imagery. Projects considered for inclusion were limited to those with a start year between 2015 and 2018 to ensure sufficient VHR imagery would be available before, during and after implementation. Obtaining at least one VHR image for each cluster before, during and after implementation enables an assessment of changes over time. Each of the selected clusters contains three or more project sites and provides an opportunity for visual analysis along one or more dimensions of ecological impact. These dimensions include erosion (i.e. near a river bank), development (i.e. near an existing village/community), crop (i.e. near crop fields), and biodiversity (i.e. near non-crop vegetation). Further, these locations provided some indication of change along these dimensions over time during a preliminary assessment using coarser (i.e. moderate to high) resolution imagery.

In Figure A1.7 Annex 1, the project site clusters are displayed on top of the overall project area in Mali Nord. Figure 4 below is an example of an individual project site cluster. The project sites are visualised alongside satellite imagery and the location of populated places, based on Open Street Maps, to provide context for how ecological impacts will be visually assessed. The populated places can be used as reference points for assessing infrastructure development and population shifts; the river banks can be used to assess erosion; the crop fields within the project sites can be used to estimate crop selection; and surrounding vegetation can be used to gauge potential impacts to broader biodiversity.

Figure 4 Example of project sites



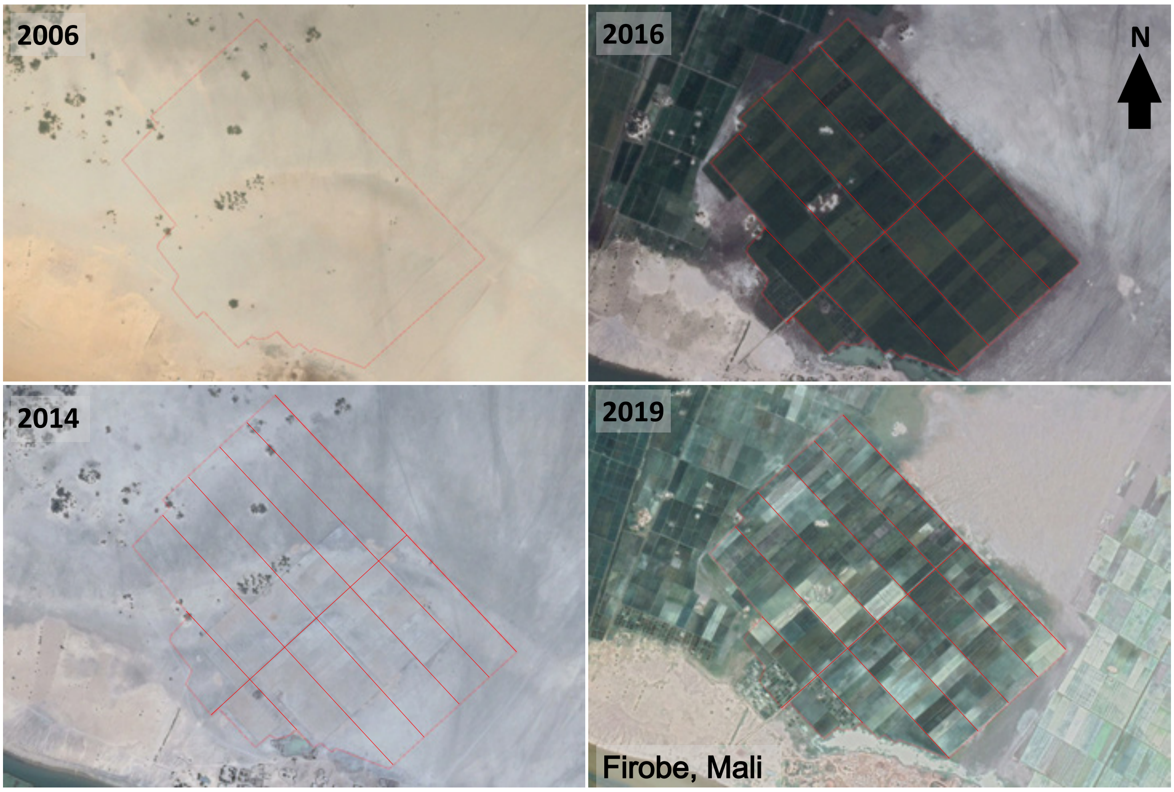
Source: authors' own figure

Note: This map shows multiple project sites in the Babagoungou region of Mali.

Visual interpretation

We utilised elements of visual interpretation (e.g. tone, shape, pattern and association) to identify ecological impacts (i.e. soil erosion, soil moisture/groundwater, development and crop diversity) within each selected project site cluster fitted out with irrigation infrastructure. The entire process was carried out in two steps. First, we overlaid each project site cluster on Google Earth Pro (GEP) to capture farm boundaries through digitisation. This was followed by the identification of ecological impacts in and around each site cluster through visual interpretation using HR PlanetScope (3 m) and VHR satellite imagery (<1 m) (see Figure 5 for an example).

Figure 5 Identification and mapping of land conversions and ecological impacts



Source: authors' own figure

Note: A project cluster near Firobe, Mali, shows gradual conversions of dry land into extensive farmland and environmental impacts over time.

Before carrying out the visual interpretation of remotely sensed satellite imagery within each project site cluster, our team overlaid the shapefile (i.e. polygon) on GEP to digitise existing farm boundaries within each project using the historical VHR imagery archive. Digitised farms helped assess the approximate percentage of the land that was cultivated land and subsequent ecological impacts within each project site cluster through the visual interpretation of HR and VHR images. The major land-cover types in the study area are grassland, uncultivated/cultivated farms, beach and water surfaces. Digitised farms were exported from GEP in KMZ format, which was later converted into shapefiles for the visual interpretation of HR and VHR imagery in QGIS software.

To visually analyse HR PlanetScope imagery, our team downloaded images (visual assets) for each year from 2016 to 2020 from *www.planet.com* and brought both digitised farm boundaries and PlanetScope imagery into QGIS. The entire process was repeated with VHR images. Similar elements of visual interpretation were utilised for mapping ecological impacts due to irrigation infrastructure. PlanetScope and VHR images from the October to December period (crop maturity) were utilized for the visual interpretation unless images were too cloudy, and in that situation, we used images from the May to June period (i.e. crop planting).

Soil erosion

The spectral reflectance of soil types in the visual part of the electromagnetic spectrum varies substantially, and colour contrast and difference in pattern between topsoil and subsoil is key to the visual interpretation of soil erosion. If the topsoil is severely eroded due to excess irrigation, a significant portion of organic matter is lost, which exposes the lighter colour of the subsoil layer.

Subsoils have considerably higher spectral reflectance than the darker colour topsoil. These variations create colour contrast in remotely sensed imagery, which can be used to detect linear soil erosion features such as rills, gullies, and stream-channels (Desprats et al., 2011). Rill erosion occurs when runoff due to excess use of irrigation water forms small, concentrated channels. Gully erosion occurs over time when a higher velocity of water (i.e. either due to high rain or excess use of irrigation without management of rills) creates larger channels that form gullies. Stream-channel erosion includes erosion of stream beds and banks, and occurs when high-velocity flows cut into the bottom of the channel, and also weakens the sides of the channel. Both aerial photographs and high-resolution imagery have been used to quantify soil erosion using visual interpretation methods (Ries and Marzloff, 2003, Sujatha et al., 2000).

Soil moisture/groundwater

Soil moisture links land surface and atmospheric processes (Babaeian et al., 2019). Spatio-temporal changes in soil moisture control the amount of water that permeates the soil and later replenishes the water table and contributes to surface runoff. Therefore, repeat soil-moisture assessments are essential to maintain the productivity of ecosystems and avoid water stress for optimal crop yield. This practice also helps schedule irrigation, avoid over-irrigation, and conserve water resources, which is often a limiting resource in sub-Saharan African countries (Tuller et al., 2019). Subsistence farming of Mali depends on rainfall (Nkonya et al., 2020), and therefore changes (increase or decrease) in rainfall may impact agricultural productivity and food security. Typically, NDWI, derived from multispectral imagery, is a reliable indicator of soil moisture. It is regularly used to assess soil moisture at larger extents. NIR and SWIR bands are inputs to develop NDWI. However, since HR and VHR imagery do not carry SWIR bands, we analysed temporal VHR images using a visual interpretation method to assess the impacts of irrigation infrastructure on soil moisture around project site clusters. Soils with high moisture tend to have high vegetation productivity (e.g. grass, shrubs) that creates visually distinguishable colour contrast and patterns. Thus, we utilised colour contrast, vegetation patterns, and hue elements to analyse soil moisture on project site clusters.

Relocation of infrastructure

Efficient utilization of irrigation infrastructure requires developing additional facilities to maximise and maintain agricultural productivity. Examples include warehouses, sheds, road networks, and often farmhouses for families and labourers. We utilised elements of photo interpretation (e.g. shape, site, association, and tone/colour) to visually analyse VHR images for exploring infrastructure relocation due to irrigation facilities on project sites (Schmitt et al., 1998). Human-made objects tend to have regular geometric shapes and are often brighter than farmland, grassland and forest cover types. “Site” refers to a topographic or geographic location on an image. This element is especially important in identifying buildings, linear features (i.e. roads), warehouses, barns, etc. Some objects in imagery appear brighter and crisper than others. For example, rectangular structures with grey to white on the ground are readily identified as buildings.

Crop diversity

Changes in crop diversity due to irrigation infrastructure on project sites were also assessed through the visual interpretation of VHR imagery. The visual interpretation of VHR imagery is considered as a bridge between remote sensing and in situ measurement approaches (Schepaschenko et al, 2019). However, it is challenging to identify crop types in an image without being in the field and comparing image objects with the ground reference data. To overcome this, we utilised the tone element of the photo interpretation technique to assess crop diversity on project sites for each time step. Farms in images that exhibited unique hues and colour contrasts were considered different crop types for measuring crop diversity. Though visual interpretation carries some uncertainty when mapping crop types, various elements have been used to estimate forest statistics directly from satellite imagery, and have successfully been used to map forest logging (Read et al. 2003), quantify forest species (Valérie and Marie-Pierre, 2006; Bilous et al., 2017), and identify tree crown (Garzon-Lopez et al., 2013).

We also leverage information from qualitative interviews with AHT Consulting project staff and a focus group with beneficiaries (farmers of Mare, PIV and PIM) to interpret the quantitative results and verify assumed causal mechanisms behind the effects.

4. RESULTS

4.1 Agricultural production

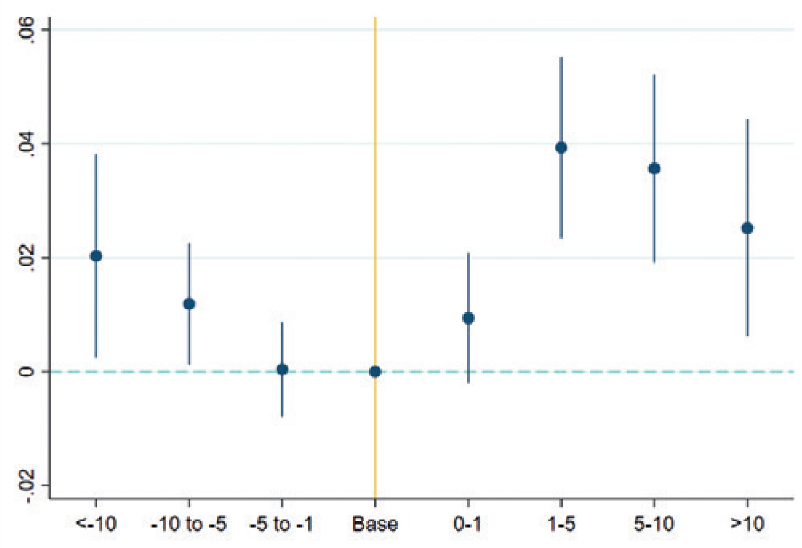
We begin by examining the impacts on remotely sensed agricultural outcomes (see Table A2.1 in Annex 2). We assess the impacts on the NDWI, which offers a useful measure of the availability of water for crop growth. The base or reference period here is years-to-treatment = -1 to 0 (i.e. the year immediately preceding the completion of irrigation). For all outcomes, we consider the treatment to commence once irrigation infrastructure was (newly) installed. We see there is no statistically significant difference in NDWI between this baseline and earlier years (years-to-treatment <-10, -10 to -5, or -5 to -1). These indicate that there do not appear to have been differential pre-trends in water availability relative to the timing of treatment, confirming that our methodology likely produces valid causal estimates. After the irrigation infrastructure is put in place, we do see statistically significant improvements in NDWI. These grow in the first year and then stabilise and remain similarly sized even 10+ years after the the installation of the irrigation, hinting at sustained maintenance and use.

We next examine the NDVI outcomes reflecting vegetation greenness (see Table A2.1, columns 2 and 3 in Annex 2). We do so for the mean NDVI in the four months immediately prior to the rainy season. We include polygon and year fixed effects, and add region-by-year fixed effects (the latter controlling for an additional level of unobserved shocks). We again observe no differential pre-trends in this measure prior to the irrigation completion, while we find a statistically significant uptick in NDVI more than one year post-completion. The increase in NDVI is relatively small (roughly 4% of the pre-rainy season mean NDVI, or 0.1 of the standard deviation (SD)), suggesting that the growing season may be extended via irrigation although not necessarily dramatically so.

We also estimate effects on mean NDVI during the traditional growing season itself (see Table A2.1 in Annex 2, columns 4 and 5). Notably, we do find some evidence of negative pre-trends here, with NDVI significantly higher in years before treatment than in the baseline reference year immediately preceding treatment. This suggests that the counterfactual trends in NDVI may have been even worse than assumed by our model, and that our impact estimates may be interpreted as lower bounds on the true effects. We do find significant increases in growing season NDVI more than one year after the irrigation is complete, and these effects appear stable between 1 and 10 years post-irrigation. These effects are large, equivalent to an increase in the mean rainy season NDVI of approximately 18% (approximately 0.3 SD). After 10 years, these effects are diminished but still distinguishable (equal to approximately 10% increase, or 0.2 SD).

Figure 6 presents these coefficients on years-to-treatment visually in an event-study graph, illustrating the decline in growing season NDVI leading up to the irrigation event, followed by the subsequent jump post-completion. Taken together, these findings provide compelling evidence that pump-based irrigation led to sustained improvements in water availability and agricultural production (see Table A2.1 in Annex 2).

Figure 6 Effect of pump-based irrigation on agricultural production in IPRODI/Mali Nord



Source: authors' own figure

Note: The figure shows the effect of pump-based irrigation (treatment) on agricultural production (proxied by NDVI) in IPRODI/Mali Nord at different year intervals, relative to the year before treatment began (base year). Each point represents the mean difference in the outcome between the year interval and the base year; each line represents the confidence interval for each point estimate. The figure is based on Table A2.1, column 4.

To understand how water constraints might lead to spillover effects across project sites (and from project sites onto other nearby sites), we add an additional dimension of variation to the above analysis. We measure the number of other active project sites located up to 20 km upstream of each individual project site. This measure is set at 0 for years in which no nearby upstream sites have yet received irrigation, and then increases as nearby upstream sites come online (the median in our panel sample is nine upstream sites). Because there are outlier observations that are located downstream from more than 100 active sites, we bin this measure into five categorical values (0.1 – <10, 10 – <50, 50 – <100, and ≥100). We then interact this measure with our time-to-treatment measures in our prior specification.

The results of this estimation show important interactions between an individual project site and its downstream neighbours (see Table A2.2 in Annex 2). First, we find that the coefficient for the direct effect of the number of active upstream sites is positive, indicating that more upstream sites generally improve NDVI, irrespective of whether the individual site itself has yet been irrigated (Table A2.2, column 1). However, these upstream sites also diminish the positive impacts achieved by the irrigation of the site itself, as the interaction effects between upstream count and years-to-treatment is negative, specifically for post-treatment years. These interactions do not wipe out the complete effect of own-site irrigation, as these impacts are still positive, but these are dampened by up to 67%. Again, this is at the same time that a greater number of active upstream sites boosts greenness for all locations. Taken together, we see some evidence of aggregate water constraints creating some spill overs in treatment effects, but the multiple channels for such effects appear to operate in opposing directions and do not immediately imply that there are negative spill overs due to the irrigation on either other treatment sites or other untreated sites.[16]

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[16] Potential channels of spillovers are addressed in 3.2.

Finally, before turning to the impacts of other investment types, we also assess whether baseline conflict conditions mediate the impacts of the PIV and PIM investments. To do so, we use the ACLED conflict data described above, which begins in 2012. We define 2012–14 as our baseline window period, and tag an irrigation site as conflict-affected at baseline if at least one conflict event occurs within 10 km of the site in this time period. We then examine the impacts of the irrigation investments for sites in which these occurred in 2015 or later, interacting the irrigation treatment status with the baseline conflict indicator. The results show that conflict does not appear to mediate the treatment effects (see Table A2.3 in Annex 2). None of the post-treatment interactions with baseline conflict are statistically significant. In fact, if anything, the coefficients on differential impacts for conflict-affected sites on growing season NDVI are positive (although these are not statistically different from zero). In other words, there is no clear evidence that the irrigation investments generate larger gains in locations with less (or more) conflict at baseline.

We next examine the impacts of mares (valorisation of floodplains) in the IPRODI/Mali Nord projects on these same remotely sensed agricultural outcomes (see Table A2.4 in Annex 2). In general, we find results that are much more muted than those for pump-based irrigation and rarely statistically distinguishable from zero. In fact, when examining the last of these estimates (those on growing season NDVI), we find some evidence of differential pre-trends, exhibiting improving NDVI in the lead-up to the irrigation installation. These same trends appear to continue post-installation, suggesting that any positive coefficients post-irrigation are likely due to the ongoing trends in these locations rather than to the irrigation itself. The event-study graph in Figure A2.1 in Annex 2 highlights the increases in NDVI experienced in the decade leading up to the irrigation's completion. Taken together, these findings do not provide evidence that the valorisation of floodplains improved water availability or agricultural production on the associated fields.

We next turn to the effects on remotely sensed agricultural outcomes associated with the projects in Sikasso (see Table A2.5 in Annex 2).[17] One important point distinguishing the Sikasso projects is that they are relatively recent; there are at most only two years of post-treatment observations possible. In terms of water availability, we again observe no meaningfully differential pre-trends in the years preceding irrigation, based on the timing of the irrigation.[18] After irrigation is installed, NDWI remains flat in the first year but rises significantly in the second year. Despite this apparent improvement in water availability, we observe no concomitant improvement in vegetation greenness during the growing season across all field-use types. In fact, we observe significantly lower NDVI for virtually all use types after the irrigation is installed (again, relative to the baseline the year preceding irrigation installation) (see Figure 7). It is not immediately clear what mechanisms drive these apparent declines, nor whether they would be sustained in the medium to long-term, but these results do suggest some cause for concern. The qualitative interviews and the focus group did not advance explanations for negative effects on productivity in Sikasso, but for why the projects might in general be less successful in Sikasso. First, the interventions in Sikasso rely largely on rainwater. Although water is stored, which makes agricultural activity less dependent on rainfall than when no irrigation is used, the amount of water available for irrigation is less under the control of the farmers than is the case with pump-based irrigation using river water. Second, the interviews suggested that the irrigation infrastructure might be less well maintained by the beneficiaries in Sikasso (weaker sense of ownership and appropriation). Unlike in IPRODI/Mali Nord, the beneficiaries do not build the infrastructure themselves and do not buy pumps to irrigate their fields. This fact may lower incentives on the part of the farmers to maintain and repair the infrastructure. However, this would only explain difference in more long-term effects. The difference might rather be in the importance of the projects to the beneficiaries. Agricultural production in the IPRODI/Mali Nord region is the main and often only source of income, which may incentivise farmers here to invest more time and resources in these projects than do those in the

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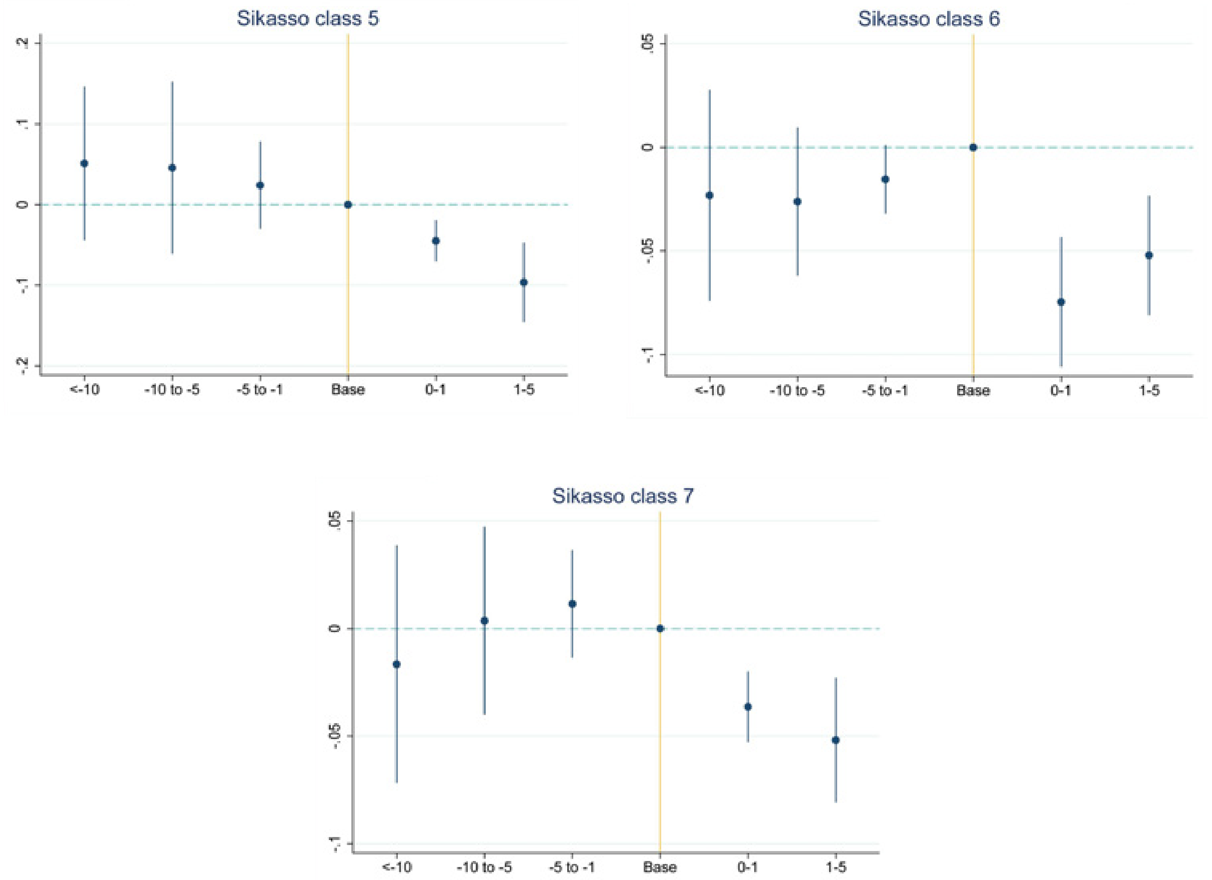
[17] Whenever no specific intervention type is mentioned, the analyses are run on all intervention types.

[18] The coefficients on NDWI in column 1 are similarly sized in all pre-treatment years.

South, where communities have other sources of revenue than agriculture. Relatedly, beneficiaries in the South might, more often than those in North, use the stored water for purposes other than irrigation.

Figure 7 Effect of irrigation on agricultural production



Source: authors' own figure

Note: These event study graphs show the effect of the valorizaton of floodplains (mares), and pump-based irrigation in vegetable and rice plots on agricultural production (proxied by NDVI) in Sikasso at different year intervals, relative to the year before treatment began (Base). Each point represents the mean difference in the outcome between the year interval and the base year; each line represents the confidence interval for each point estimate. The figures are based on Table A2.5 in Annex 2 (top left graph is based on column 2, top right on column 3 and the figure below on column 4).

4.2 Child nutrition and health

We expect that a key effect of irrigation is increased food security (H1a) and improved food composition (H1b), as well as the treatment effect of the intervention on child nutrition and health (H1c). Using data from the LSMS, we do not find effects of treatment on either hunger or the ability to vary food (see Table A2.6 in Annex 2), which can be explained by two reasons First, the food security indicators measure the experience of the entire household, while positive nutritional changes often accrue to an observable effect more quickly among children than adults, as short-term investments have a greater potential for impact (see e.g. Fernald et al., 2008, Mary et al., 2020). Second, food security is a very broad measure. Relative food security could increase and people could feel less hungry than they were previously. However, when asked about hunger in general, they could still feel hungry and reply yes when surveyed. Based on these analyses, we cannot confirm the hypotheses that households in treatment locations are more food secure than those in control locations (H1a) or that households in treatment locations show a better food composition than those in control locations (H1b).

However, we do find substantial and significant improvements in child health (H1c) that are plausibly linked to food security and food composition. We analyse effects of IPRODI/Mali Nord projects on different child health outcomes and under-5 mortality, using a DID framework. Child stunting, wasting, lower body mass and occurrence of anaemia are based on biometric DHS data. Measures of child mortality such as birth weight and occurrence of diarrhoea and fever and cough are based on mothers' reporting to the DHS their living children born in the past five years. Treatment effect is defined as treatment before birth for stunting, wasting, body mass and birth weight, reflecting impacts that occur prior to birth, such as improved maternal health and prenatal nutrition. Treatment on child mortality is defined as treatment before age 5, meaning a child is considered to have received treatment if the nearest project site was cleared at any point before the child turned 5 years. For the health outcomes of birth weight and child illnesses (anaemia, diarrhoea, fever, cough) treatment is defined as treatment before survey, reflecting the impact of investments in child health that occur throughout early childhood, including postnatal investments in child health and nutrition.

Child stunting

We first consider the effects of IPRODI/Mali Nord projects on child stunting, wasting and body mass. These are the measures most suitable to test H1c as they are plausibly linked to food security and composition of the mother's diet before her child's birth, and because these biometric data, measured by enumerators, are less susceptible to measurement error than reported measures.

The treatment effect of IPRODI/Mali Nord projects prior to birth on child stunting is reported in Table A2.7 in Annex 2.[19] There is a consistent significant positive effect of irrigation on height-for-age among children living 0–4 km from the project site, suggesting that child stunting decreases as a result of the intervention near to project locations, the effect being slightly larger among children living 2–4 km from a project site than among those living 0–2km from a project site. The treatment effect on height-for-age for those living 4–6 km from project sites is consistently negative across all three measures, although it is only significant when height-for-age is measured as standard deviations or as a percentage of the reference median. This suggests that child stunting increases as a result of irrigation in the 4–6 km distance band (see Figure 8).

The results on child stunting consistently indicate that IPRODI/Mali Nord projects reduce child stunting in areas closest (0–4 km) to project locations. This suggests that irrigation has a significant impact on child health in areas proximate to project sites. Although we cannot identify the mechanism by which these reductions in stunting occur for this group of children through the DHS, the LSMS shows in section 4.3 that quality of calories is a key driver in nutrition gains that result in improved height-for-age. This confirms that treatment likely boosts either food security (H1a) or food composition (H1b) in areas close to project sites and so also supports H1c.

One potential explanation for these reversed, negative effects on child stunting 4–6 km from the project locations suggested in qualitative interviews with project staff and beneficiaries is population movement toward project sites of healthier individuals in search of better economic prospects. Another possibility is a shift of economic activity to project locations, but this explanation is not

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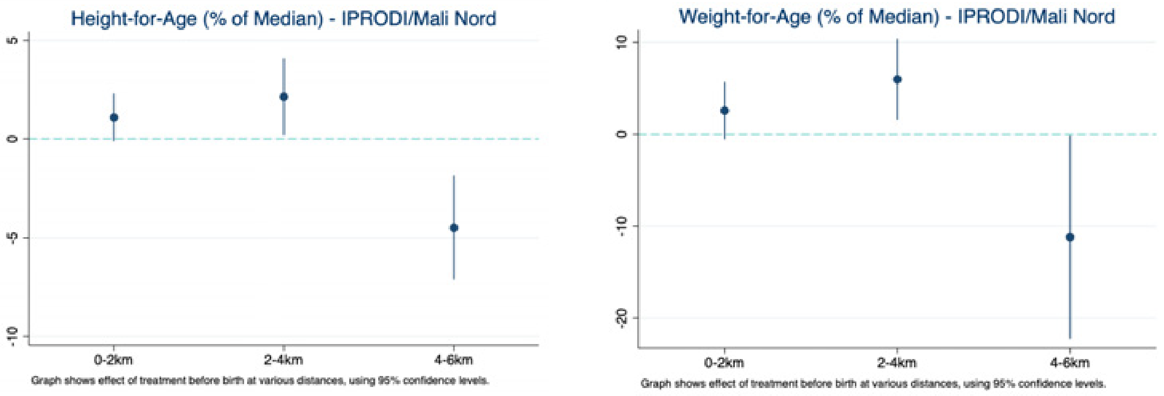
[19] In Table A2.7 and A2.8 column 1 reports the effect on height-for-age as a percentile, column 2 reports the effect on height-for-age as standard deviations of the reference median, and column 3 reports the effect on height-for-age as percent of the reference median. The results are broadly similar across all three measures.

confirmed by our analysis of VRH data reported in section 4.6. Lastly, the negative effects at further distance might be a function of negative spillovers. We assess this possibility by interacting treatment with binary and count measures on other project sites within a 20 km reach. The results indicate that the positive effects of treatment might indeed be dampened as the number of completed nearby projects increases (see Table A2.8 in Annex 2).[20] However, the positive effect on height-for-age are substantial in size so that many projects would have to be completed within a 20 km range for negative spillovers to compromise the positive impact from project proximity on child stunting. Because the likelihood of many projects within 20 km of a household is low, the benefits remain more likely for children within 4 km of projects than negative spillover impacts.

A possible channel for negative effects is the competition over the use of river water. However, project documentation, including ex-post-evaluations and interviews with project staff and beneficiaries suggest that the amount of water used for irrigation by project beneficiaries is too small to affect the availability of water to farmers at distances of the projects of 4–6 km. The interviews, as well as the NDVI results reported in Table A2.2 in the Annex, rather suggest a potential positive effect of nearby projects on agricultural production (and potentially also child health) before a project begins in the studied location. Interviews suggested that farmers involved in the projects may sell seeds or share other agricultural inputs with farmers living in locations that only become project sites later on in our sample.

Figure 8 Effect of treatment before birth on child stunting and child wasting



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child stunting (height-for-age) in the left graph and child wasting (weight-for-age) in the right graph at different distance bands from the project location. Both outcomes are reported in percent of the reference median. Treatment is considered nearby project completion prior to birth. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The left graph on child stunting is based on Table A2.9, column 3 and the figure to the right for child wasting is based on Table A2.10, column 3.

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[20] Table A2.8 reports the same strong positive effect of irrigation on child stunting at the 2-4km distance band. The 0-2km band has similar coefficients as the significant coefficients in Table A2.7, therefore there is still likely a positive effect for children at the 0-2km distance. However with more controls in this analysis, other variables have more explanatory power, and thus decrease the relative significance of the 0-2km treatment band.

Child wasting

The effects on child wasting are similar to those on child stunting (see Figure 8) and suggest that child wasting decreases as a result of the interventions 2–4 km from project locations.[21] In areas closer to project locations (0–2 km), the results are less consistent across the three measures of child wasting used: although the coefficient on the treatment effect is positive for this group across all three measures, it is only significant when weight-for-age is measured as standard deviations from the reference median (see also Table A2.10, Figure A2.6 and A2.8 in Annex 2).

Like child stunting, we again find that treatment negatively correlates with weight-for-age at further distance (areas 4–6 km from the project sites). This is consistent across all three measures of weight-for-age, suggesting that child wasting increases as a result of the irrigation interventions in these areas, although it is only significant when using the weight-for-age measure of standard deviations or percentage of the reference median. The results are also largely robust to defining treatment as treatment before survey (see Table A2.11 and Figure A2.7 in Annex 2).[22]

Child body mass

There is no significant effect of treatment (before birth or before survey) on child body mass at any distance band, regardless of how body mass is measured (see Table A2.13, Figure A2.9, Table A2.14, Figure A2.10 and Figure A2.11 in Annex 2). Overall, this suggests that although irrigation had a significant effect on both child wasting and stunting, there is not a similar significant effect on body mass. There are several possible explanations for this. First, it may be that gains among children in height and weight were similar enough that body mass was not dramatically affected. For instance, a child who is severely stunted and wasted is likely also underweight; if the child's nutrition improves enough to boost their height and weight simultaneously, their level of stunting and wasting may decrease while they remain underweight. Second, the effects of treatment may be concentrated among children who were not severely underweight prior to treatment. We would expect gains in height and weight to reduce low body mass most among children who are severely underweight; if the gains are instead concentrated among those who are closer to a normal weight, we may see appreciable improvements in stunting and wasting but not in body mass.

Low birth weight

The treatment effect on low birth weight is reported in Table A2.15 in Annex 2. There is a negative and significant impact of treatment on low birth weight for children 2–4 km from project sites, suggesting that the interventions reduced the incidence of low birth weight in this area. However, there is no statistically significant effect of irrigation on low birth weight in either the 0–2 km or 4–6 km distance bands, although the point estimates are both negative (see Table A2.15, Figure A2.11 in Annex 2).The lack of statistically significant treatment effects for the 0–2 km and 4–6 km bands may be due to the small sample size and relatively low quality of birth weight data. Among children living within 6 km of

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[21] Column 1 reports the effect on weight-for-age as a percentile, column 2 reports the effect on weight-for-age as standard deviations of the reference median, and column 3 reports the effect on weight-for-age as percent of the reference median. In areas closer to project locations (0–2 km), the results are less consistent across the three measures: although the coefficient on the treatment effect is positive for this group across all three measures, it is only significant when weight-for-age is measured as standard deviations from the reference median. In areas 4–6 km from the project sites, there is a negative treatment effect on weight-for-age across all three measures, suggesting that child wasting increases as a result of interventions in these areas, although it is only significant when using the weight-for-age measure of standard deviations or percent of the reference median.

[22] Regardless of the measure used, treatment before survey has a positive and significant effect on weight-for-age among those who live 0-2 km from project sites, suggesting that the projects reduce child wasting in these areas. In addition, for those 2–4 km from project sites, there is a positive coefficient on treatment for all weight-for-age measures, although it is only significant when considering percentile. Although the coefficients of the treatment effect for the 4–6 km distance band are negative, they are not statistically significant.

a project site, 87.5% had no reported birth weight, in large part because mothers reported that the majority of children (79.1%) were not weighed at birth. Among those children who had a reported birth weight, the quality of data on birth weight may also be imperfect, as only 36.0% of women who reported a birth weight used a birth card, while the remainder reported the weight from recall. Furthermore, regardless of the source of information used to report a birth weight, the density was focused on salient weights (2.5 kg, 3 kg, 3.5 kg), with 41.8% of reported weights falling on one of these points, suggesting that reported birth weights were usually rounded. As such, it may be the case that we are not able to capture the true treatment effect with these data.

Child mortality

To assess effects on child mortality, we use a binary variable that is 1 if the child had died by age 5 and 0 if the child was alive at their fifth birthday. Treatment in this case is defined as treatment before age 5, meaning a child is considered to have received treatment if the nearest project site was cleared at any point before the child turned 5 years. We limit this sample to children who were born at least 5 years prior to the date their mothers were surveyed. The estimated treatment effect on child mortality is reported in Table A2.16 in Annex 2 (see also Figure A2.12 in Annex 2). There is no effect of the interventions on child mortality for those who live within 0–4 km of the project site, but there is a small negative effect (-0.0888) on child mortality for those who live 4–6 km away from the project site. This suggests that there may be small improvements in overall child survival for those who live further from IPRODI/Mali Nord project sites.

Even so, the overall impact of the projects on child mortality is small. This result is not surprising for two main reasons. First, the expected impact of irrigation projects on child health is primarily through the mechanism of improved nutrition, both in the form of more calories and better quality of calories. Although malnutrition plays an important role in child mortality, it is not the sole factor and, as such, child mortality as a whole may not have a dramatic response to improved irrigation even in the presence of improved nutrition. Second, to fully understand the impact of IRPODI/Mali Nord projects on child mortality, we must define treatment as treatment before age 5, as any intervention before age 5 may reduce child mortality. However, interventions that occur later in a child’s life have less potential to reduce mortality, simply because that mortality may have already occurred. As such, the overall treatment effect may mask the potential for treatments to boost child mortality among those who are very young at the time of infrastructure completion.

In addition to the reported results on child health, we also investigated potential effects on childhood illnesses that are more loosely – if at all – linked to nutrition. The projects did not consistently affect the prevalence of diarrhoea or anaemia.[23] They only showed a moderate increasing effect in fever and cough, potentially resulting from more exposure of villagers to infectious diseases as a result of increased social interactions due to the projects (see Table A2.17 in Annex 2). However, these effects are not consistent across distance bands.

Our findings with regard to food security and child health suggest that both child stunting and child wasting decrease as a result of treatment in areas proximate (0–4 km) to project locations, supporting H1c. Since child stunting and child wasting is driven in large part by the quantity and quality of calories consumed by children, this therefore also provides evidence that irrigation projects increased food security (H1a) and/or food composition (H1b) for children living within 4 km of project sites.

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[23] While anemia may be positively affected by food high in iron, it is unlikely to be affected by the types of crops studied here.

4.3 Economic well-being

We use multiple measures from the LSMS to assess the impact of proximity irrigation projects on household income, production, consumption and food security. All of these measures are self-reported by the head of household. While these self-reported measures are somewhat limited, they offer insight into potential mechanisms for the impact of access to irrigation on improved child health outcomes.

We consider the effect of IPRODI/Mali Nord projects on measures of economic well-being through a DID framework. The entire sample of households has at least one irrigation project within 6 km by 2020. Data on project location and the time of irrigation installation are used in conjunction with data on survey cluster location and year to determine if a cluster had a project within 6 km at the time of survey. Treated households have projects within 6 km at the time of survey. Untreated households do not yet have an irrigation project running within 6 km at the time of survey.

Income, production, consumption and food security

We do not find an effect of irrigation on agricultural or total income for households within 6 km of a project site (see Table A2.18 and Figure A2.13 in Annex 2). This null effect is not surprising for two reasons. First, each measure of household and total income is self-reported, which increases the likelihood of measurement error. Additionally, subsistence farmers make up most of Mali's agricultural population. Therefore, any small increase in the quantity or quality of agricultural output is likely to have consumption benefits for the household's children before additional output is sold and reported as household income. It is plausible for hungry children to be given extra or better food before the crops are sold for additional income, especially in light of our results on reduced child stunting and wasting closer to projects. In conclusion, our results do not support the hypothesis that households in treatment locations have a higher income than those in control locations (H2). The effect of the interventions on the sale value, kilograms sold, and kilograms consumed of all crops is shown in Table A2.19 in Annex 2 (see also Figure A2.14, Table A2.20 and Figure A2.15). There is no effect of irrigation on kilograms sold or consumed. However, there is a positive effect on crop sale value for households within 2 km of a project site. Because of this difference, it is likely that a shift in the quality of agricultural output is driving better health outcomes, rather than quantity. Crop quality improvements could be in the form of better-quality production of crops which were already being planted, or in a crop type shift. Without a panel dataset, however, we cannot make a decisive claim about the type of crop-quality improvement.

Null effects for the 2–4 km and 4–6 km treatment bands are not surprising. Quality improvements in the same crops previously planted would likely yield small increases in prices, especially due to low agricultural output prices in Mali. Therefore, there would have to be large quality increases for these crops to cause large enough value changes for a significant effect. The largest quality changes are most likely to occur at the 0–2 km treatment bands. Additionally, there is a wide variety of crops in the crop sale-value measure. For the case in which households switch to better-quality crop types, all of the other crop sales are still included in the measure. We cannot separate the better-quality crops from the others. Consequently, unless the sale value of the quality crops increases substantially, we will not see the effect due to the noise from all the other crops. In this case as well, the largest change in crop quality is most likely to have a significant effect, making the 0–2 km treatment band the first place in which an effect would be seen.

The significant effect of irrigation on crop sale value without any significant effects on agricultural income has a plausible explanation. Agricultural income is a measure generated from every source of agricultural income, including tree products, livestock and animal products. These factors are unlikely to be as affected by irrigation as crops. Therefore, it is likely that noise from these other agricultural products covers up the significant positive effect we would expect to see from improved-quality crops in the agricultural income and total income analyses.[24] The shift to higher-quality crops is likely a result of a crop-type shift instead of improvements in previously grown crops. Without a panel dataset, we cannot identify the exact crop-type shifts taking place. However, we have identified cotton, Mali's largest cash crop, as more relevant to the projects in the Sikasso region than the Mali Nord projects used here. Bamako, Segou and Sikasso are the primary cotton-growing regions of Mali and are all south of the projects used here. While cotton is not the relevant shift which occurs, other high-value and quality crops likely experience a shift to higher prominence in the areas closest to the projects. Therefore, there is some evidence for the hypothesis that crop diversity is higher in treatment than in control locations (H5c). The lack of treatment effect on both hunger and ability to vary food can be attributed to several factors, in addition to measurement error from self-reporting (see Table A2.6 in Annex 2). First, both of these food security indicators measure the experience of the entire household, while only child health outcomes have significant improvement. As previously mentioned, children are likely the first in a family to benefit from better food access. Therefore in the case of a small improvement in food, children's food security and thus health outcomes could improve, while the rest of the household experiences no substantial increase in food security.

Second, food security is a very broad measure. Relative food security could increase and people could feel less hungry than they were previously. However, when asked about hunger in general, they could still feel hungry and reply yes when surveyed. Finally, food variety might not be the first investment people make from improved crop sales. Investment in more calories instead of more variety is a likely scenario, especially as diets to which people are accustomed require time to change.

In conclusion, we cannot confirm the hypotheses that households in treatment locations are more food secure than those in control locations (H1a) or that households in treatment locations show a better food composition than those in control locations (H1b). Strong positive effects in child health outcomes close to the projects lead us to believe that children are likely more food secure and show a better food composition, but we do not have evidence to formally support this hypothesis.

Household assets and dwelling quality

We consider the effect of IPRODI/Mali Nord projects on household assets and dwelling quality, as a proxy of household income and economic wellbeing. We utilise measures of asset ownership and household dwelling quality collected in the DHS household survey. These measures include ownership of durable household goods, including radios, televisions and refrigerators, ownership of transportation goods, including bicycles, motorcycles/scooters and cars/trucks, and household dwelling characteristics, including electricity and finished walls and roofs. Many of these measures, including durable goods ownership, transportation asset ownership and electricity use, are self-reported for the household. However, some household dwelling characteristics, including roof and floor material, are observed and reported by the survey enumerator. This mix of outcomes allows us not only to investigate a number of household assets and dwelling characteristics that might be affected by changes in household income, but also to complement reported measures with observed measures that are less vulnerable to measurement error.

Our sample for the household assets and dwelling quality analysis is limited to households that were surveyed as part of the household survey in any of the five most recent waves of the DHS. When household asset ownership is considered, assets owned by any member of the household are counted toward household ownership. As the latest DHS wave was collected in 2018, prior to the take-off of

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[24] The effect of the projects on the same production and consumption variables is reported in Table A2.20. However, only millet, sorghum, rice, and corn data are used here in order to standardise the measurement. Figure A2.20and Table A2.19 have the same number of observations as any household involved in agriculture grows one of these four main food crops. We analysed these four main crops with similar values per kilogram to minimise the noise from crops with different values per unit of measurement. The lack of a significant effect on crop sale value at the 0–2 km treatment band is the main difference in Figure A2.20 as opposed to Table A2.19. This change shows that any increase in crop sale value is not related to these four main food crops.

projects in the Sikasso region, our household asset and dwelling quality results are limited only to IPRODI/Mali Nord project sites.

We first consider the effect of IPRODI/Mali Nord projects on household ownership of three common durable consumer goods – radio, television and refrigerator. We select these goods for two primary reasons. First, an increase in household income as a result of irrigation projects may translate into increased ownership of these assets in the short term. Second, as these goods are not used for agricultural purposes, it is unlikely that household ownership of these goods is caused by the irrigation projects in ways other than through an increase in income. The outcome variable for each of these measures is a binary variable that is 1 if the good is owned by any member of the household and 0 otherwise. There is a significant negative effect of treatment on radio ownership 4–6 km from project sites, but there is no significant effect in areas closer (0–4 km) to project locations, as shown in Table A2.21 and Figure A2.16 in Annex 2.[25] Overall, these results suggest there is little effect of IRPODI/Mali Nord projects on household ownership of durable consumer goods. This may occur despite increased crop sale value if households choose to spend the increased returns on other investments or goods. For example, households may choose to spend additional income on increased child nutrition or additional agricultural inputs before purchasing the household assets we consider. Furthermore, we may not see an increase in household ownership of more expensive durable goods, such as televisions and refrigerators, due to extremely low rates of adoption in local communities. Among our untreated sample, only 9.8% of households own a television and only 1.7% of households own a refrigerator, indicating that these assets are unlikely to be early investments when households receive additional income.

The negative effect of treatment in the 4–6 km band on radio ownership may reflect a decrease in disposable income within this distance band as a result of treatment. Radio ownership is fairly common in our sample: among untreated households in this distance band, 67.8% own a radio. As such, it is clear that radio is often prioritised when disposable income is available. It is therefore reasonable that a decrease in income resulting from treatment could result in decreased ownership of radios. However, we should not place too much emphasis on this result, as there is no overarching negative effect on durable consumer goods across all three measures for this distance band.

We next consider the effect of IPRODI/Mali Nord projects on household ownership of three transportation assets – bicycle, motorcycle/scooter and car/truck. As baseline ownership of these goods is low and the cost to purchase these goods is high, an increase in household income as a result of irrigation projects may translate into increased ownership of these assets in the longer term. However, we must be cautious when considering the mechanism by which any treatment effect occurs, as transportation goods may be used to transport agricultural goods to market and, as such, may affect agricultural income. The outcome variable for each of these measures is a binary variable that is 1 if the transportation asset is owned by any member of the household and 0 otherwise. The treatment effect of IPRODI/Mali Nord projects on transportation asset ownership is presented in Table A2.22 and Figure A2.17 in Annex 2. There is no effect of treatment on bicycle or car/truck ownership in any of the distance bands. There is a significant negative impact of treatment on motorcycle/scooter ownership in the 2–4 km distance band, suggesting that treatment reduced ownership of these items in this area. However, there is no effect on motorcycle/scooter ownership at 0–2 km or 4–6 km from the project sites.

Overall, these results suggest there is little effect of IPRODI/Mali Nord projects on household ownership of transportation assets. This may occur despite increased crop sale value near the project sites due to extremely low rates of adoption in local communities. Among our untreated sample, only

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[25] The treatment effects on ownership of these three assets are reported in Table A2.21. Column 1 reports the effect of treatment on radio ownership. The treatment effect on television and refrigerator ownership are reported in columns 2 and 3, respectively. There is no significant effect of treatment on television or refrigerator ownership at any distance band.

11.8% of households own a bike, only 13.5% own a motorcycle or scooter, and only 1.2% own a car or truck, indicating that these assets are unlikely to be early investments when households receive additional income. Furthermore, due to the costs of these assets, increases in income as a result of the intervention may not be large enough to affect ownership of household transportation assets.

We next consider the effect of IPRODI/Mali Nord projects on household dwelling quality, utilising three measures from the DHS, within a DID framework. The first measure is whether the dwelling has electricity, which is self-reported. The other two measures – whether the household has a finished roof (e.g. metal, wood, tile or shingle) and whether the household has finished walls (e.g. cement, stone, brick, wood plank) – are observed by the enumerator. An increase in household income as a result of irrigation projects may translate into increased dwelling quality in the longer term. The outcome variable for each of these measures is a binary variable that is 1 if the dwelling has quality in question (i.e. has electricity, a finished roof, finished walls) and 0 otherwise. The treatment effect on household dwelling quality is presented in Table A2.23 in Annex 2 (see also Figure A2.18 in Annex 2). Column 1 reports the treatment effect of IPRODI/Mali Nord projects on electricity use within the household dwelling. There is no significant effect on electricity use in any of the distance bands. Column 2 reports the treatment effect on finished roof material at the household dwelling, and column 3 reports the treatment effect on finished wall material at the household dwelling. There is a significant positive effect on finished roofs in areas 2–4 km from treatment locations, but a significant negative effect on finished walls in these areas. However, there is no significant effect on either finished roofs or walls in the 0–2 km or 4–6 km distance bands. Despite opposite effects on finished roofs and walls in the 2–4 km band, there is no overall effect on dwelling quality in this distance band, when taking all measures of dwelling quality into account.

Overall, these results suggest there is little effect of IPRODI/Mali Nord projects on household dwelling quality. This is consistent with the null findings on household assets across all distance bands. Overwhelmingly, it appears that IPRODI/Mali Nord projects had no effect on household asset ownership or dwelling quality. This may be evidence that the economic gains of these projects were not sufficient enough to allow households to purchase more assets or invest in dwelling quality. However, it may also be the case that economic gains were large but were applied to other areas, such as nutrition or investment in agricultural inputs.

Employment

We consider the effect of IPRODI/Mali Nord projects on individual employment, as a proxy of income and economic wellbeing. We utilise measures of employment collected in the DHS men’s and women’s survey from adult respondents. The first measure of employment we use assesses whether a respondent is currently working, defined as having performed any work other than housework in the past seven days. Since work is broadly defined, this measure of employment includes a variety of employment types, including formal and informal employment, paid-in-cash, paid-in-kind and unpaid work, and work for traditional employers, family or self. The second measure of employment we use assesses whether a respondent is employed in agriculture, based on reported occupation for work over the past 12 months. Similar to our measure of employment, our measure of agricultural employment is broad and includes formal and informal work, paid-in-cash, paid-in-kind and unpaid work, and for self, family or someone else.

Our sample for the employment analysis is limited to men and women who were surveyed as part of the men’s and women’s survey in any of the five most recent waves of the DHS. Since the DHS surveys more women than men, our sample is primarily female. We conduct the employment analysis on the entire sample, as well as on the male and female sub-samples. This is because the expected employment and income effects of irrigation projects may differ by gender, due to gender differences in land ownership, crop selection and occupational choice. Since the latest DHS wave was collected in 2018, prior to the completion of the installation of irrigation infrastructure in the Sikasso region, our employment results are limited only to IPRODI/Mali Nord project sites. We first consider the effect of IPRODI/Mali Nord projects on current employment. The treatment effects on employment are reported in Table A2.24 and Figure A2.19 in Annex 2. There is a positive impact of irrigation on male employment 2–4 km from project sites. However, there is no significant effect on female employment in this distance band. In addition, there is no significant effect on employment in the 0–2 km or 4–6 km distance bands. These results suggest that there may have been employment gains concentrated among men 2–4 km from project sites. However, these results are not consistent across all areas close to project sites.

We next consider the effect of IPRODI/Mali Nord projects on agricultural employment. These results are presented in Table A2.25 and Figure A2.20 in Annex 2. There is a positive effect of treatment on agricultural employment in areas 2–4 km from project sites, but not at other distance bands. In addition, this effect is not consistent when we consider the effects across genders.

This suggests that there may be some gains to agricultural employment as a result of projects in the 2–4 km range, reflecting a boost to the agriculture sector in these areas. However, the results are not consistent across genders and are not significant for areas closer to project sites. This may reflect the coarse nature of the agricultural employment data available in the DHS. If, for instance, the shift of workers from other sectors into agriculture is relatively small but income among those in the agriculture sector increases, we would not observe the full effect on the agriculture sector using this measure. We perform additional analysis on employment outcomes to consider whether there is a differential impact of the interventions on current and agricultural employment for those respondents who belong to more pastoral ethnic groups, as compared to those who belong to less pastoral ethnic groups. Each respondent in the DHS self-reports their ethnic group, which allows us to assign a variable of pastoralism based on the ancestral characteristics of the reported ethnic group. This is particularly relevant as the irrigation interventions may have differential impacts on employment across ethnic groups, depending on groups' involvement in pastoralism versus sedentary farming.

We generate a pastoral value for each ethnic group in the DHS by replicating McGuirk and Nunn (2021), in order to characterise the likelihood that a respondents' ethnic group is traditionally engaged in pastoralism. This approach uses data from the *Ethnographic Atlas,* a database of 1 265 ethnic groups assembled by Murdock between 1962 and 1980. We replicate McGuirk and Nunn's pastoral variable to analyse the interaction between pastoralism and irrigation projects for our research context. Their pastoral variable was originally developed by Becker (2019). Our pastoralism variable combines information on the percentage of animal husbandry in which the ethnic group participates (on a 0–1 scale, v4 in the *Ethnographic Atlas*) and a binary indicator variable for whether or not the ethnic group's most important large animal can be herded (v40 in the *Ethnographic Atlas)*. The results of our employment analysis with pastoral interactions are presented in Table A2.26 and Figure A2.21 in Annex 2. We do not find that there is any significant moderating effect of pastoralism on the treatment effect. This result likely reflects the coarseness of our employment measures.

4.4 Women's empowerment

We expect that a key effect of irrigation is an increase in women's decision-making power (H3a), particularly in areas with higher shares of women farmers (H3b). The DHS women's survey collects self-reported measures of women's decision-making power in a number of domains. In addition, the women's survey collects respondents' opinions of IPV across a number of hypothetical situations, a commonly used indicator of female empowerment. Use of these two measures allows us to assess the impact of projects on women's decision-making power and empowerment (H3a). Since the DHS does not collect community information on the share of farmers that are female, we consider the moderating role that matrilineality plays in the effect of the projects on women's decision-making power and empowerment.[26] Information on matrilineality is derived by matching women's reported ethnicities from the DHS to ancestral characteristics from the *Ethnographic Atlas*, and is a useful proxy for female participation in agriculture, as women's land rights and ability to inherit agricultural land are influenced by ancestral norms surrounding matrilineality.

We consider the effect of IPRODI/Mali Nord projects on women's decision-making power and opinion of IPV, as a proxy of women's empowerment. Our measures of decision-making power are based on DHS questions from the women's survey that ask women who usually make decisions in four domains: spending the woman's own income, the woman's own healthcare, large household purchases, and family visits. Our measures of women's opinion of IPV, which we use as a proxy for women's empowerment, are based on DHS questions from the women's survey that ask women whether it is acceptable for a husband to beat his wife in five hypothetical scenarios: the wife goes out without the husband's permission, the wife neglects the couple's children, the wife argues with her husband, the wife refuses sex with her husband, and the wife burns food. For both decision-making power and opinion of IPV, we also create summary indices that aggregate the results of the component questions.

Our sample for the women's empowerment analysis is limited to women that were surveyed in any of the four most recent waves of the DHS, as the full set of decision-making and opinion on IPV questions was only introduced to the Mali DHS in the 2001 wave. Since the latest DHS wave was collected in 2018, prior to take-off of projects in the Sikasso region, our employment results are limited only to IPRODI/Mali Nord project sites.

The treatment effect of IPRODI/Mali Nord projects on women's self-reported decision-making power is reported in Table A2.27 in Annex 2. Column 1 reports the treatment effect on the female decision-making power summary index, while columns 2 to 5 report the treatment effect on each of its four components: women's decision-making with respect to spending own income (column 2), own healthcare (column 3), large household purchases (column 4), and family visits (column 5). Due to the multiple testing hypothesis, the summary index is the most reliable measure, and attention should be paid primarily to these results in column 1.

There is no significant treatment effect of IPRODI/Mali Nord projects on the female decision-making index in any of the three distance bands (see also Figure A2.22 in Annex 2). This may be because there is no true effect of the projects on the women's decision-making, or it could be because the effect is too small to detect with our current sample size. In addition, the measure of decision-making used in our analysis is inherently fairly coarse due to the way decision-making is reported in the DHS. When asked about various types of decisions, a woman reports who makes each decision. This is then converted into a binary variable that is 1 if a woman has any role in the decision (i.e. sole or joint decision-making power) and a 0 if she has no role. As such, this measure of decision-making may not pick up small changes in decision-making power.

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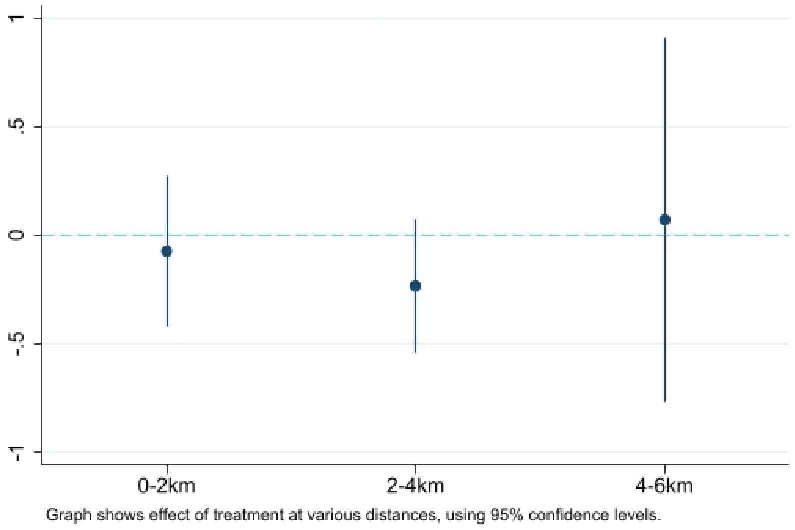
[26] Some of the plots near the irrigation sites are dedicated to female farmers, but these were not comprehensively reported. These data quality issues prevented us from analysing the percentage of female farmers as a covariate or dimension of heterogeneity.

Figure 9 Effect of irrigation on women's opinion of IPV



Source: authors' own figure

Note: This figure shows the estimated treatment effect on women's acceptance of violence against women at different distance bands from the project location. This outcome is a summary index of responses about acceptance of a number of different types of violence against women. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.28.

In addition to women's self-reported decision-making power, we also consider the effect of treatment on women's acceptance of abuse through the IPV – a commonly used proxy of female empowerment. It reports on women's opinion of whether a husband is justified in beating his wife if she goes out without his permission, neglects their children, argues with him, or refuses sex with him (see Table A2.28 and Figure 9). There is a significant negative effect of IPRODI/Mali Nord projects on women's opinion of IPV in areas 2–4 km from project sites, suggesting that treatment reduces women's belief that IPV is justifiable in these areas (only statistically significant at the 10% level, however). As opinion of IPV is a proxy for women's empowerment, this suggests that the interventions may have boosted women's empowerment in areas 2–4 km from project locations. There is no significant effect of treatment on this index in the 0–2 km or 4–6 km distance bands. However, the coefficient is positive for areas 0–2 km from project sites and negative for those areas 4–6 km from project sites, a pattern that is consistent with the findings on child stunting and wasting.

This suggests that the projects may have increased female empowerment in areas proximate to project sites (H3a). However, the results are not conclusive. As with the decision-making power measures, the IPV opinion measures from the index are inherently coarse. Women can only report whether they think it is justified, it is not justified, or they do not know. Based on these answers, we construct a binary variable that is 1 if the woman believes it is justified and is 0 otherwise. As such, we may not be able to capture small shifts in female empowerment using this index. Any effects of IPRODI/Mali Nord projects on women's decision-making power and empowerment are likely strongest in areas where women are more involved in agriculture and, as such, can directly reap a greater economic benefit from the projects. Since the DHS does not collect community information on the share of farmers that are female, we instead consider the moderating role that matrilineality plays in how the interventions affect women's empowerment. Matrilineality is an imperfect but useful proxy for female participation in agriculture, as women's land rights and ability to inherit agricultural land are influenced by ancestral norms surrounding matrilineality. We derive information on matrilineality by matching women's reported ethnicities from the DHS to ancestral characteristics from the *Ethnographic Atlas*. The effects of this analysis are reported in Table A2.29 and Figure A2.23 in Annex 2. Among those 0–2 km from project sites, it appears that the effects of treatment on women's decision-making power are stronger for those from more matrilineal backgrounds. However, for those 2–4 km from project sites, there is a negative coefficient on the interaction term, suggesting the effects of treatment on women's decision-making power are weaker for those from more matrilineal backgrounds. There is no significant moderating effect for those 4–6 km from project sites. In addition, there is no significant moderating effect of matrilineality on the treatment effect on women's opinion of IPV in any of the distance bands. Given that the significant results of this analysis appear only for decision-making power, for which we previously found no significant treatment effect, we do not find these results particularly meaningful.

4.5 Conflict

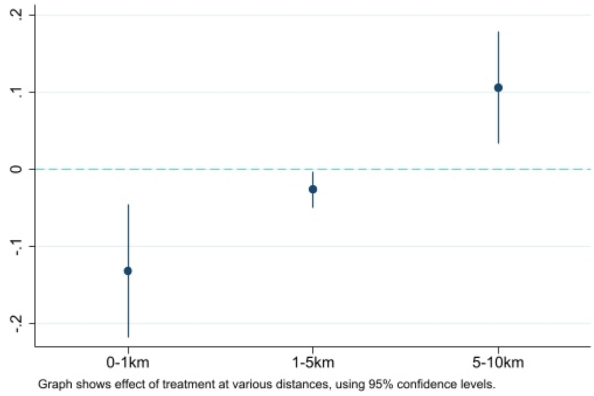
We expect that a key effect of the irrigation interventions is lower conflict risk/intensity (H4). Conflict risk and intensity are difficult to evaluate on the whole due to the nature of available conflict data. Even so, rich data exists on the number and location of conflict events that occurred in Mali in the past several decades. As such, we utilise georeferenced conflict event data from ACLED to investigate the effect of the projects on conflict risk/intensity. Although the collected conflict events do not capture all elements of conflict risk, they are a concrete proxy. In addition, although the count nature of the data does not reflect the intensity of each conflict event, conflict events do capture intensity in terms of frequency of events.

To determine the effect of the studied interventions on conflict, we conduct a DID analysis for each of the three main project types considered in this paper: IPRODI/Mali Nord pump-based irrigation (PIV and PIM), IPRODI/Mali Nord Mares, and Sikasso. First, we consider the effect of treatment on yearly conflict events reported by ACLED. This data covers the years 1997 to 2021. The results of this analysis are reported in Table A2.30 in Annex 2 and illustrated in Figure 10.

The treatment effect of IPRODI/Mali Nord pump-based irrigation on conflict is presented in column 1 of Table A2.30 in Annex 2 and in Figure 10 (Panel A). There is a significant and fairly large negative impact (-0.132) of treatment on the number of conflicts occurring annually within 1 km from these project sites, suggesting that the interventions decreased conflict events in the immediate surrounding area. In other words, after the installation of the irrigation infrastructure, the risk of a conflict event decreased by an average of 0.132 conflict events, roughly ⅓ of a SD, a large and meaningful impact. In addition, there is a significant but smaller negative impact (-0.026) of treatment on conflict 1–5 km from these project sites, suggesting that irrigation decreased conflict in the greater surrounding area, up to 5 km. However, there is a significant and positive impact (0.105) of treatment on conflict 5–10 km from these project sites (roughly 0.25 SD), suggesting that treatment increased conflict at further distances.

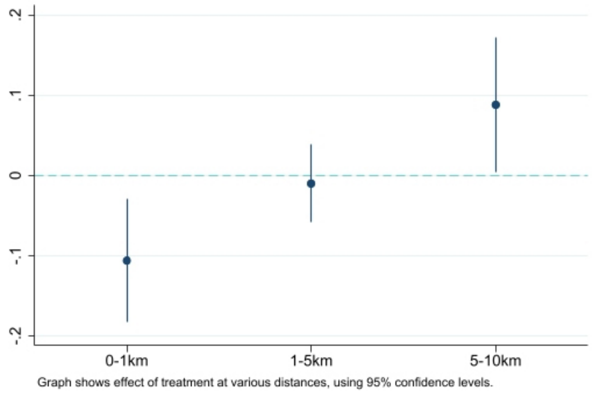
Figure 10 Effect of irrigation on yearly conflict events

Panel A: IPRODI/Mali Nord Pump-Based Irrigation



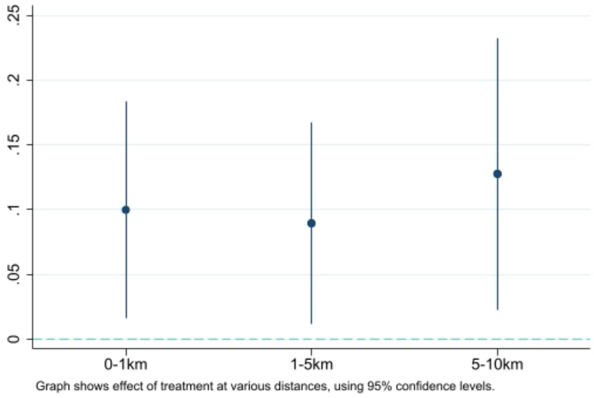
Graph shows effect of treatment at various distances, using 95% confidence levels.

Panel B: IPRODI/Mali Nord Mares



Graph shows effect of treatment at various distances, using 95% confidence levels.

Panel C: Sikasso



Graph shows effect of treatment at various distances, using 95% confidence levels.

Source: authors´ own figure

Note: This figure shows the shows the estimated treatment effect on yearly conflict events at different distance bands from the project location. Treatment in Panel A is pump-based irrigation, in panel B) flooded area/mare and in panel C all irrigation types in Sikasso. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based onTable A2.30.

The treatment effect of IPRODI/Mali Nord Mares on conflict is presented in column 2 of Table A2.30 in Annex 2 and in Figure 10 (Panel B). As with pump-based irrigation, there is a significant and fairly large negative impact (-0.106) of mares on conflict 0–1 km from these project sites, suggesting that treatment decreased conflict events in the immediate surrounding area. In addition, there is no significant impact of treatment on conflict 1–5 km from these project sites, suggesting that the positive effect of treatment dissipated with distance from the project sites. In addition, similar to the results on pump-based irrigation, there is a significant and positive impact (0.128) of the valorisation of floodplains on conflict 5–10 km from these project sites, suggesting that projects increased conflict at further distances.

These results suggest that IPRODI/Mali Nord projects reduced conflict in the areas immediately surrounding the project site, providing evidence that conflict risk/intensity decreased as a result of the interventions in areas proximate to project locations (H4). The interviews and focus group suggested that project sites might suffer less from violence than other villages in the surroundings, because rebels have no incentives to attack sites that contribute to better living conditions for the population they are largely supported by. In addition, the farmers themselves – as they are busy working and as their living conditions improve – have fewer incentives to join an armed group for a living. However, this effect diminishes with distance from the project site, and at greater distances the effect on conflict even turns positive. Indeed, areas 5–10 km away from IPRODI/Mali Nord project sites saw an increase in violence as a result of the interventions. The reason for this increase in conflict further away from project sites is not entirely clear. It is possible that conflict relocated from areas near project sites to those further away as a result of the interventions; an explanation that was regarded as plausible by some of the interviewees, but not all. Finally it is also possible that grievances among individuals 4–6 km away spurred additional conflict in this area or that relocation of economic activity toward project sites may have increased economic insecurity among those further away, leading to increased conflict over resources.

The treatment effect of Sikasso projects on conflict is presented in column 3 of Table A2.30 in Annex 2 and in Figure 10 (Panel C). Unlike for IPRODI/Mali Nord projects, the effect of the Sikasso projects is significant and positive at all three treatment bands, suggesting that there was an increase in conflict events as a result of Sikasso projects (Table A2.30, column 3). The positive effect of treatment for those 0–1 km and 1–5 km away from project sites (0.0999 and 0.0895, respectively) is smaller than for those who are 5–10 km away (0.128). These results suggest that Sikasso projects differed substantially from IPRODI/Mali Nord projects in their effects. It is not clear why treatment is correlated with an increase in conflict in Sikasso. One speculation may be that the characteristics of projects carried out in Sikasso differed significantly enough from IPRODI/Mali Nord projects to cause this divergence in treatment effect. For instance, perhaps the benefits of projects were less equitably distributed in Sikasso, leading to increases in land-related conflict. Another speculation may be that the two regions of Mali differed in some way that led similar irrigation projects to have markedly different outcomes. For instance, rainfall and farming patterns differ significantly between Sikasso and Northern Mali. Perhaps some regional characteristic led to a difference in how well-received irrigation projects were by the local community and, as such, whether they attracted or discouraged future conflict.

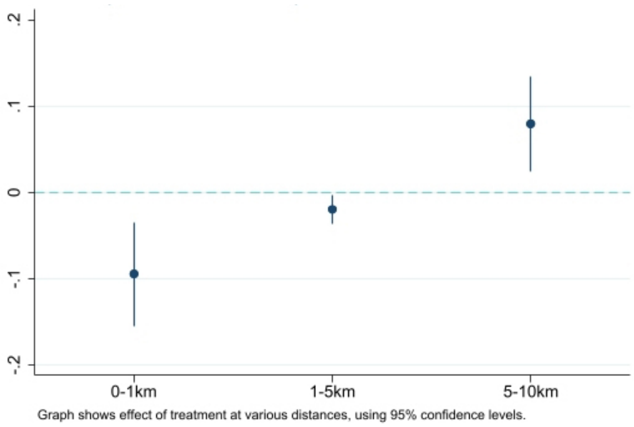
To better understand the effect of treatment on conflict, we narrow our definition of conflict to exclude conflicts involving one or more state actors. This better elucidates whether treatment had an effect on the types of conflict that we would most expect to change as a result of irrigation projects, mainly small-scale local conflicts. We repeat the same analysis, limiting our conflict outcome to yearly non-state conflict events. The treatment effect of IPRODI/Mali Nord pump-based irrigation on non-state conflict are presented in column 1 of Table A2.31 in Annex 2 and in Figure 11 (Panel A). Overall, the effect on non-state conflict is similar to the effect found on conflict more generally, although the coefficients are slightly attenuated. There remains a significant negative effect (-0.0946) on non-state conflict in areas 0–1 km from project sites, a significant but small negative effect (-0.0197) on non-state conflict in areas 1–5 km from project sites, and a significant positive effect (0.0797) on non-state conflict in areas 5–10 km from project sites.

Similarly, the treatment effect of IPRODI/Mali Nord Mares projects on non-state conflict is similar to the effect of these projects on conflict more generally, but again with attenuated coefficients. These results are presented in column 2 of Table A2.31 and in Figure 11 (Panel B). There is a significant negative effect (-0.0667) of the interventions on non-state conflict in areas 0-1 km from project sites, no significant effect for areas 1–5 km from sites, and a significant positive effect (0.0630) on non-state conflict in areas 5–10 km away from project sites. These results suggest that the conflict effects of IPRODI/Mali Nord projects was broad and not limited to state actors. The interventions seem to have reduced small-scale conflict close to project sites (H4), but led to an increase further away.

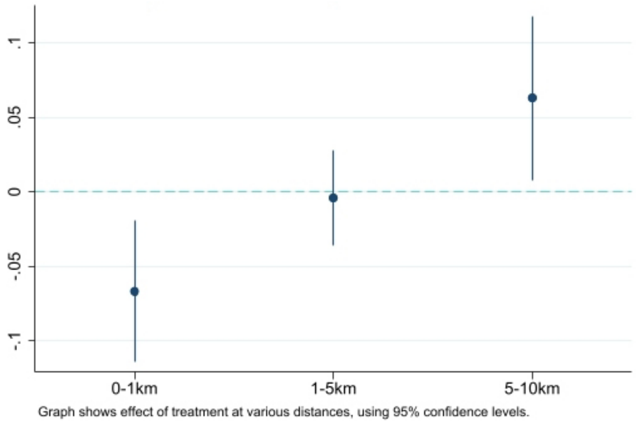
The treatment effect of Sikasso projects on non-state conflict (Table A2.31, column 3 in Annex 2 and Figure 11, Panel C) differs significantly from the estimated effect on overall conflict. We do not observe a treatment effect of Sikasso projects on non-state conflict in any of the distance bands. This suggests that the increase in conflict caused by the interventions is driven by state-related conflict. It is not entirely clear why this effect might occur. One theory may be that national police forces are more likely to get involved in disputes over farmland in the south of Mali. If this is the case, local land-related conflict may be reported as state conflict (Norwegian Institute of International Affairs, 2021). The irrigation project may also have induced an increase in grievances toward the state, expressed near the projects. Alternatively, we cannot rule out that irrigation sites were differentially selected for those that were treated earlier in more conflict-prone locations, even though neither project documentation nor our interviews with project staff hinted at this explanation.

Figure 11 Effect of irrigation on yearly non-state conflict events

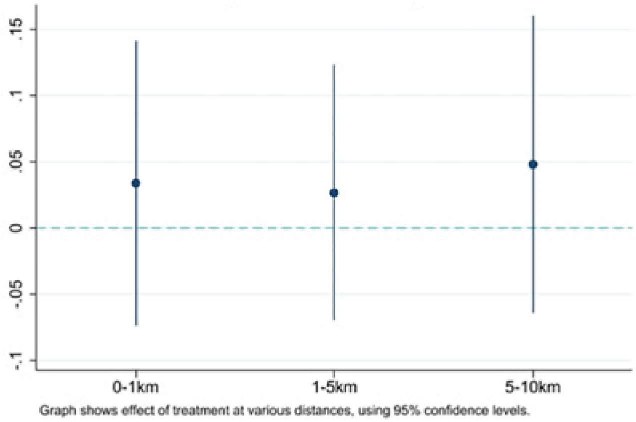
Panel A: IPRODI/Mali Nord Pump-Based Irrigation



Panel B: IPRODI/Mali Nord Mares



Panel C: Sikasso



Source: authors´ own figure

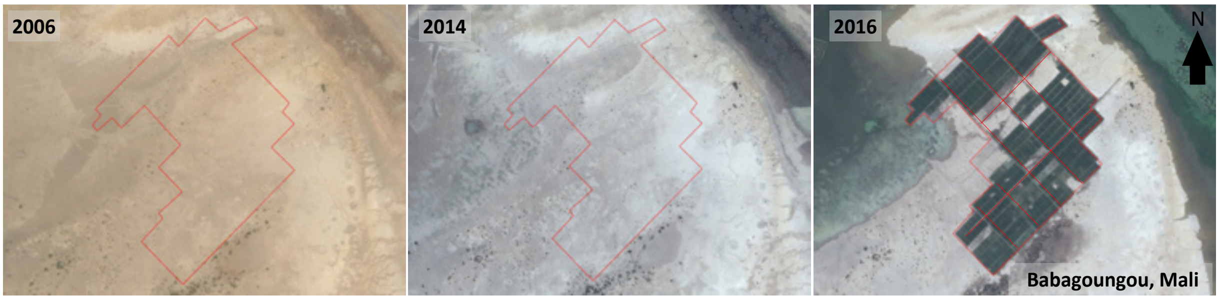
Note: This figure shows the estimated treatment effect on yearly conflict events that do not involve one or more state actors at different distance bands from the project location. Treatment in Panel A is pump-based irrigation, in panel B) flooded area/mare and in panel C all irrigation types in Sikasso. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.31.

4.6 Environmental conditions

The visual interpretation of HR imagery suggests that farm boundaries on grasslands in the vicinity of the Niger River were established, starting 2006, long before irrigation infrastructure. Grassland conversions into farmland and partial cultivation began as early as 2009 (e.g. Ambiri and Sebi Femmes) and continued to increase with irrigation interventions that also accelerated grassland conversion into farmland in the vicinity of rural settlements (e.g. Firobe project site clusters; see Figure 4).

Our analysis suggests that regular cultivation on farmland occurred only after the irrigation interventions, with a few exceptions (i.e. three out of eight project site clusters). For example, project clusters such as Aglal, Singama and Tissikinen were cultivated partially for a few years before interventions. Outcomes suggest that the Aglal clusters were fully cultivated a year before the start of the irrigation system in 2015. Likewise, ~25% of Singama and Tissikinen projects were cultivated in 2013, but irrigation infrastructure started in 2016 and 2017, respectively. The Chirfina (2015 – irrigation start year) and Sébi Femmes (2017 – irrigation start year) project clusters were partially cultivated for the first two years after the installation of irrigation infrastructure (see Figure 12).

Figure 12 Cultivation of farms



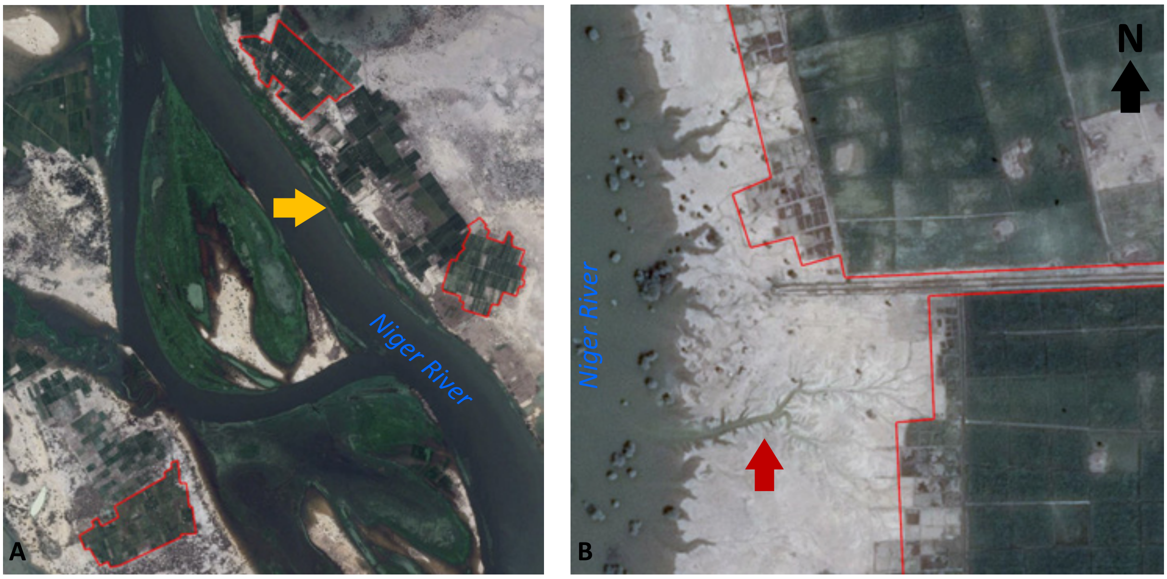
Source: authors' own figure

Note: The figures show that farms were cultivated to their full extent four years after the completion of the irrigation system at the Babagoungou project.

Soil erosion

Excessive irrigation often leads to soil erosion that can be evident through the contrast between bare soil and grass/shrub-covered land surfaces. The visual interpretation of VHR satellite imagery showed a small extent of soil erosion at >60% project clusters (i.e. Tissikinen, Singama, Ambiri, Chirfina and Firobe) in the form of rills, gullies and channels. Soil erosions at many sites were due to the presence of high sub-surface water and due to the proximity to the Niger River. Many of these project site clusters showed algal bloom at the edge of the Niger River (Figure 13 – left). Gully erosion is an indicator of soil erosion. Aglal, Sébi Femmes and Tissikinen clusters are located near the Niger River where there are a few stream channels due to the seasonal flow of water from the river. Singama and Chirfina project clusters have experienced a huge expansion of farmland since the start of irrigation infrastructure, with a few minor soil erosions that led to algal bloom in stream channels made by the flow of seasonal water from the river. Gully erosions are also present at Ambiri and Firobe project clusters. Whether these gullies are due to excess irrigation or the flow of rainwater in the river is not clear through the VHR imagery analysis (see Figure 13 – right). Regardless, expansion of farmland around some of these project clusters (e.g. Singama, Chirfina, Tissikinen and Firobe) suggests the success of irrigation interventions.

Figure 13 Sporadic algal bloom due to soil erosion caused by excessive irrigation



Source: authors' own figure

Note: The figure shows the effects of irrigation on erosion. (Left) The presence of algal bloom at the Niger riverbanks (yellow arrow) indicates the leaching of nutrients and organic contents from farmland due to soil erosion. (Right) Excessive water from over-irrigation and rain caused gully erosion (red arrow).

Soil moisture/groundwater

The visual analysis of VHR imagery suggests high soil moisture at and around the project clusters during the farming season (August to October) that, in some cases, continued to March of the next year (see Figure 14). Prior to the irrigation interventions, many of these clusters were grassland and showed the presence of moisture only during the overflow of the Niger River, and high water in the stream channels due to the flow of water from the river. Soil moisture on project clusters has increased throughout the year over time since the start of irrigation interventions. For example, Babagoungou project clusters showed high soil moisture on farms that was not there before the start of irrigation infrastructure. However, through the visual interpretation, it is not clear if soil moisture on some project clusters (e.g. Aglal, Tissikinen, Singama and Firobe) is due to shallow riverbanks of the Niger River and normal rainy seasons or from irrigation interventions. For example, the Singama project cluster often showed high soil moisture throughout the year around the riverbanks before the interventions, which could be due to the high groundwater table and/or shallow riverbanks.

Figure 14 Soil moisture on and around the farmland

Source: authors' own figure

Note: Singama and Chirfina project clusters show the presence of high soil moisture on and around the farmland. Yellow arrows indicate the presence of soil moisture.

Relocation of infrastructure

Development activities near to farmland are a common phenomenon after the irrigation interventions. However, the visual interpretation of VHR images of project clusters did not show the relocation or development of infrastructure other than that related to irrigation interventions, such as dirt roads and a few minor canals. Every project cluster showed the development of dirt roads after the irrigation interventions and after the expansion of farmland. The visual analysis of Aglal and Tissikinen project clusters showed a few structures near to farmland, but those were there before interventions. One of the reasons for the lack of development of facilities could be the presence of rural settlements near to project clusters. For example, project clusters (e.g. Aglal, Sébi Femmes, Ambiri and Firobe) are located near rural settlements that provide residents with easy access to their farmlands (see Figure 15). The lack of development could be attributed to farmlands in the Niger River floodplain often experiencing flooding during the rainy season and also to high soil moisture.

Figure 15 Expansion of rural development in the vicinity of farmland

Source: authors' own figure

Note: Firobe project clusters show the presence of rural settlements in the vicinity of farmland. Yellow arrows indicate the presence of rural settlements near farmland.

Crop diversity/ biodiversity

Visual interpretation of VHR images indicates that crop diversity has improved since the irrigation interventions were started in the study area. Since visual analysis does not offer a methodology that can help to detect crop types (e.g. rice versus maize, millet and sorghum), differences in the hue of farms were used to count the number of different crops sown on the project clusters. Visual analysis suggests that every project cluster had six to eight different crop types, including orchards in the vicinity (see Figure 16). The highest number of different crop types (approximately seven) was present on Singama and Tissikinen project clusters.

Figure 16 Crop diversity

Source: authors' own figure

Note: Project clusters show the highest crop diversity in Singama and Tissikinen project clusters compared to others such as Chirfina.

5. DISCUSSION

5.1 Summary of the findings

Agriculture in the Sahel is largely rainfed, and the rural economy of the Sahel is strongly dependent on rainfall patterns. As climate change reduces the predictability of rainfall and increases need for agricultural irrigation in face of rising temperatures, agricultural communities across the Sahel become increasingly vulnerable to rainfall shocks and the socioeconomic consequences of such shocks. Irrigation has the potential to increase community resilience to climate change by boosting agricultural productivity, reducing poverty, and increasing social stabilisation. As such, GDC has invested in several irrigation projects for climate change adaptation in Mali. To this end, the interventions developed an approach that focuses on the interactions of multiple vulnerabilities in the Malian agricultural sector, as well as its exposure to climate-related hazards over a period of more than 20 years. These irrigation projects include a mix of small-scale pump-based irrigation, large-scale gravitation-based irrigation, and the valorisation of floodplains. While project activities remain relatively similar over time, the theory of change has become more complex so that GDC in Mali follows a broad and holistic approach to strengthen resilience with these irrigation interventions. Our analysis considers how this mix of projects directly affects social, economic and environmental development and contributes to broader social, ecological and economic resilience. Specifically, we consider how these projects affect food security and food composition, related child health, income, women's decision-making power, conflict risk/intensity and ecological impacts. This analysis utilised data on pump-based irrigation and the valorisation of floodplains.

We first consider how German-funded irrigation projects in Mali affect agricultural productivity. Theoretically, these irrigation projects improve agricultural resilience to rainfall shocks, including both absence and fluctuations of precipitation, by increasing access to water for irrigation even independent of rainfall. This increased accessibility to water and resilience to rainfall shocks translates into increased agricultural productivity. Using remotely sensed outcome measures, we find that pump-based irrigation in IPRODI/Mali Nord yielded substantial gains in agricultural production. These gains begin in the season following the completion of the irrigation infrastructure and continue over the ensuing 10 or more years. We find substantial increases in water availability prior to the rainy season, as well as in the vegetation greenness both prior to and during the rainy season.

We next consider how these irrigation projects affect food security and food composition. Theoretically, the improved agricultural productivity conferred by irrigation projects improves the quantity and variety of crops grown by farmers, including both subsistence and commercial farmers. In addition, certain irrigation projects, such as the valorisation of mares, allow for increases in fish farming. As such, we hypothesise that irrigation will increase food security (H1a), food composition (H1b) and child health (H1c). We use both reported survey measures and biometric measures of child nutrition and health from the DHS to consider the effect of the projects on food security and food composition in project areas. We find that both child stunting and child wasting decrease as a result of treatment in areas proximate (0–4 km) to project locations. Since child stunting and child wasting is driven in large part by the quantity and quality of calories consumed by children, this therefore provides strong evidence that irrigation projects increased food security (H1a) and/or food composition (H1b) for children living within 4 km of project sites. Interestingly, we find that these positive effects of the interventions on child nutrition do not extend to areas 4–6 km from project sites. Indeed, it appears that irrigation projects led to an increase in child stunting and wasting in this further distance band. These effects warrant future research.

We next consider how irrigation projects in Mali affect income. Theoretically, the increase in agricultural production conferred by irrigation projects allows commercial farmers to earn greater agricultural income from crop sales. As such, we hypothesise that irrigation will increase income (H2). Crop sale value increased for households within 2 km of completed projects, while income did not increase for households within 2 km of completed projects. This difference is not surprising, as crop sale value is more reflective of changes that result from agricultural improvement, while income consists of many other factors such as animal and tree production. As the interventions studied have no effect on kilograms of crops produced and sold, it appears that the change in crop sale value comes from a shift to higher-quality crop types, rather than an increase in quality or quantity of the four main food crops.

We find no consistent effects on overall employment or household assets via these survey data. We do find small increases in agricultural employment in the 2–4 km bands, suggesting some possible shifts by men into more intensive farming from other occupations as a result of the irrigation. However, these are not accompanied by broader increases in overall employment rates or similar shifts among women. We also consider whether the improvements in agricultural production identified via our remote sensing measures allowed households to invest in more or higher-quality assets or make improvements to their homes. Across all household assets and dwelling quality measures, we find no consistent changes due to the irrigation interventions. It appears that the gains in agricultural production were sufficient to improve child nutrition, but consistent with the earlier results on crop sales and overall income, households did not experience other material gains.

By expanding agricultural production opportunities and improving children's nutrition, the irrigation interventions could have boosted women's empowerment in the affected communities (H3a), especially those where women could share in these expanded opportunities (H3b). We therefore assess whether irrigation increased women's decision-making power within their households, and altered women's views of IPV. We find no consistent effects on women's overall decision-making power, but we do identify changes in their views of IPV for those who were 2–4 km away from the irrigation sites. The introduction of irrigation leads these women to view IPV as more problematic and less frequently justified, suggesting some limited improvement in women's empowerment and the potential to positively impact gender equality due to the irrigation.

Since considerable social conflict is driven by worsening resource scarcity, the improvements in agricultural production due to the irrigation could be theorised to dampen subsequent conflict episodes (H4). In fact, we do find significant reductions in conflict events in the immediate surroundings of the IPRODI/Mali Nord PIV and PIM sites. At the same time, conflict events appear more likely to occur in the peripheral surroundings (4–6 km) of completed irrigation sites, suggesting that conflict may have shifted rather than declined overall. In the case of Sikasso, where agricultural production appears to have fallen following the irrigation completion, we also observe spikes in conflict episodes (although we have far fewer observations post-irrigation and much rarer conflict events in general in this region).

Unlike all the other outcomes studied, we can only leverage descriptive results on ecological impacts of the interventions for a small sample of sites, based on very high resolution remote-sensing data. We hypothesised that irrigation may minimise the ecological impacts of changes in hydrological regimes on ecosystems by reducing the risk of soil erosion by water (H5a), improving soil moisture (H5b), and increasing crop diversity (H5c). The visual interpretation of VHR images suggests that soil erosion due to excessive irrigation frequently occurred around project clusters. Seasonal gully and stream-channel soil erosion may have led to algal bloom at the Niger riverbanks. However, whether these erosions are due to excess irrigation or the flow of rainwater from farms to the river is not clear through the VHR imagery analysis. Surface water availability increases soil moisture that may vary throughout the year; therefore, increased soil moisture at the project clusters could be attributed to irrigation interventions (H5b). However, whether the evident soil moisture on some project clusters was because of the high water table, precipitation or irrigation interventions requires further analysis. Irrigation interventions increase cropping intensity (i.e. number of crops per year) and diversity (i.e. number of crop types per year) with low to moderate conversions of farmland to developed uses that could be a reason for increased crop diversity at the treatment locations (H5c). Crop diversity has improved substantially since the irrigation interventions. Visual analysis of VHR images before and after irrigation interventions suggests that crop types have increased after the irrigation interventions across the studied project clusters. Contrary to our expectations, relocation of developmental activities on or near project clusters was a rare phenomenon, except the construction of dirt roads after the irrigation interventions and the expansion of farmland. This could be attributed to the location of project clusters on floodplains that often experience flooding and high soil moisture during the rainy season. In addition, the lack of development of facilities could be the presence of rural settlements near to project clusters.

The present evaluation found improvements in agricultural production, child nutrition and moderate improvements regarding income of the target population and gender equality as a consequence of irrigation funded by GDC. These improvements likely reduce the vulnerability of farming communities in rural Mali towards drought and erratic rainfall. Our analyses of agricultural production cover a comparatively long time frame and show sustainable effects, fulfilling an important pre-condition for reduced vulnerability to translate into resilience. However, the ultimate test for the extent to which irrigation contributes to beneficiary communities' climate resilience will be droughts and erratic rainfalls that are predicted to increase in intensity and frequency in the future. In addition, our results suggest that climate vulnerability and therefore most likely also resilience of households at further distances from project sites might be negatively affected through project activity. These unintended negative developments should be further investigated when drawing implications from the results presented in this evaluation for future programming of these and similar interventions.

5.2 External validity

Our study sample covers several ecological regions of Mali, including those in the country's drier north, as well as the semi-tropical south. The findings from the IPRODI/Mali Nord project sites could therefore reasonably be applied to other parts of the Sahel, including parts of Niger, Nigeria, Burkina Faso, Senegal and Chad. Our study sample covers roughly two decades and includes recently completed projects as well as much older ones, as well as observations both prior to the 2012 coup and in the more than eight years that have since passed. We can thus be reasonably confident that similar results would be obtained. The time period studied includes considerable rainfall variability, meaning our findings are likely to be applicable to extreme rainfall patterns in future. At the same time, these findings are specific to areas where rainfed yields are quite low (in Mali's case, mean cereal yields are frequently below 2 tonne/ha), and thus would not readily apply to areas that are less water-constrained. Our findings also do not necessarily extend to other types of irrigation interventions – including large-scale gravity schemes – since we see gains only due to pump-based irrigation but not the valorisation of floodplains.

The evaluated interventions represent a typical case of infrastructure investment by German development cooperation (GDC) in climate change adaptation. Climate finance is an important part (25%) of GDC and half of climate finance is dedicated to adaptation to climate change (Noltze and Rauschenbach, 2019). The interventions studied lie at the intersection of two adaptation-relevant development sectors – water and agriculture – which, together with environmental protection, include the largest number of projects and the largest financial volume of German adaptation finance (Noltze et al., 2023a). Moreover, climate vulnerable countries such as Mali lie at the heart of the allocation of Germany's adaptation finance (Noltze and Rauschenbach, 2019). This is especially true for German financial cooperation by the KfW, with many similar interventions in other parts of the Sahel region, e.g. the valorisation of floodplains in Burkina Faso. Finally, the intervention type under study is also typical, as infrastructure investments are one of the dominant types of German adaptation interventions (compare Doswald et al., 2020) and has a high level of effectiveness when dealing with shocks and stressors and enhancing adaptation capacities internationally (Noltze et al., 2023a, 2023b).

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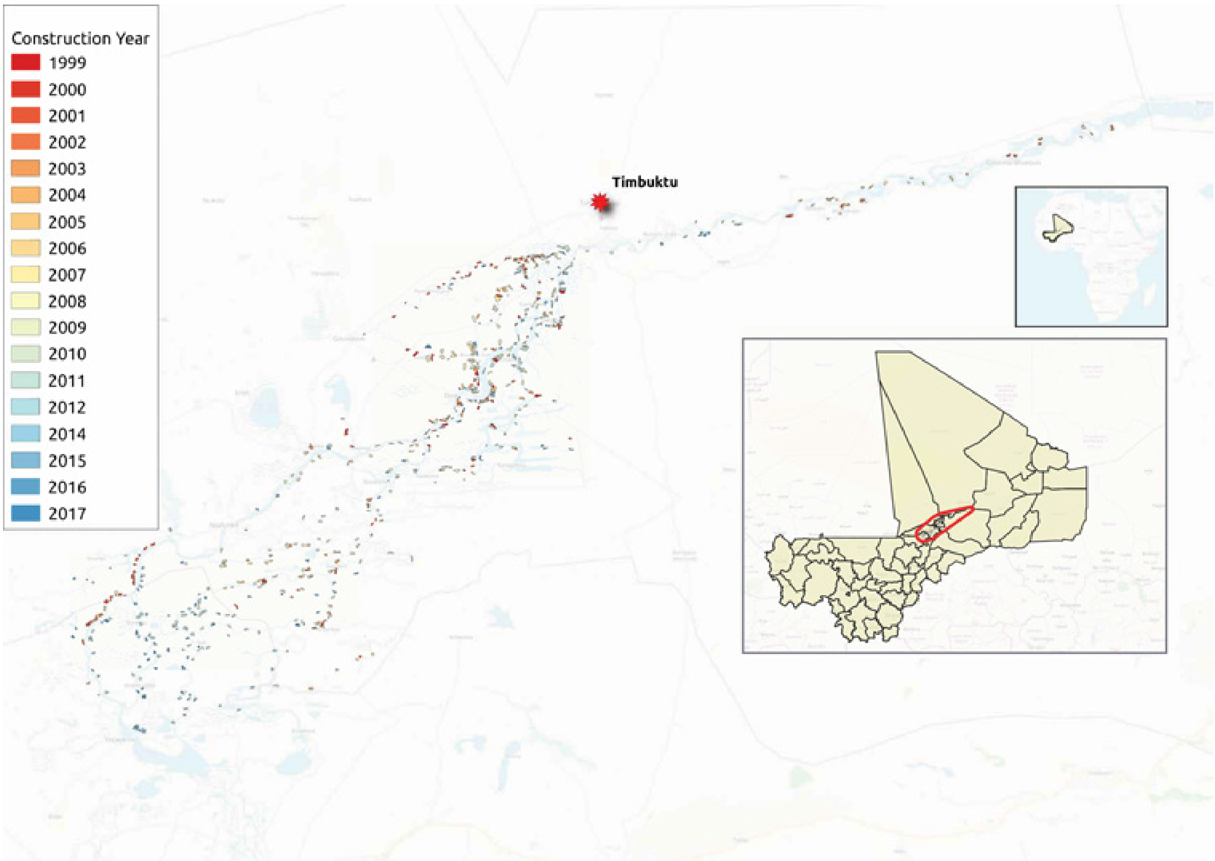
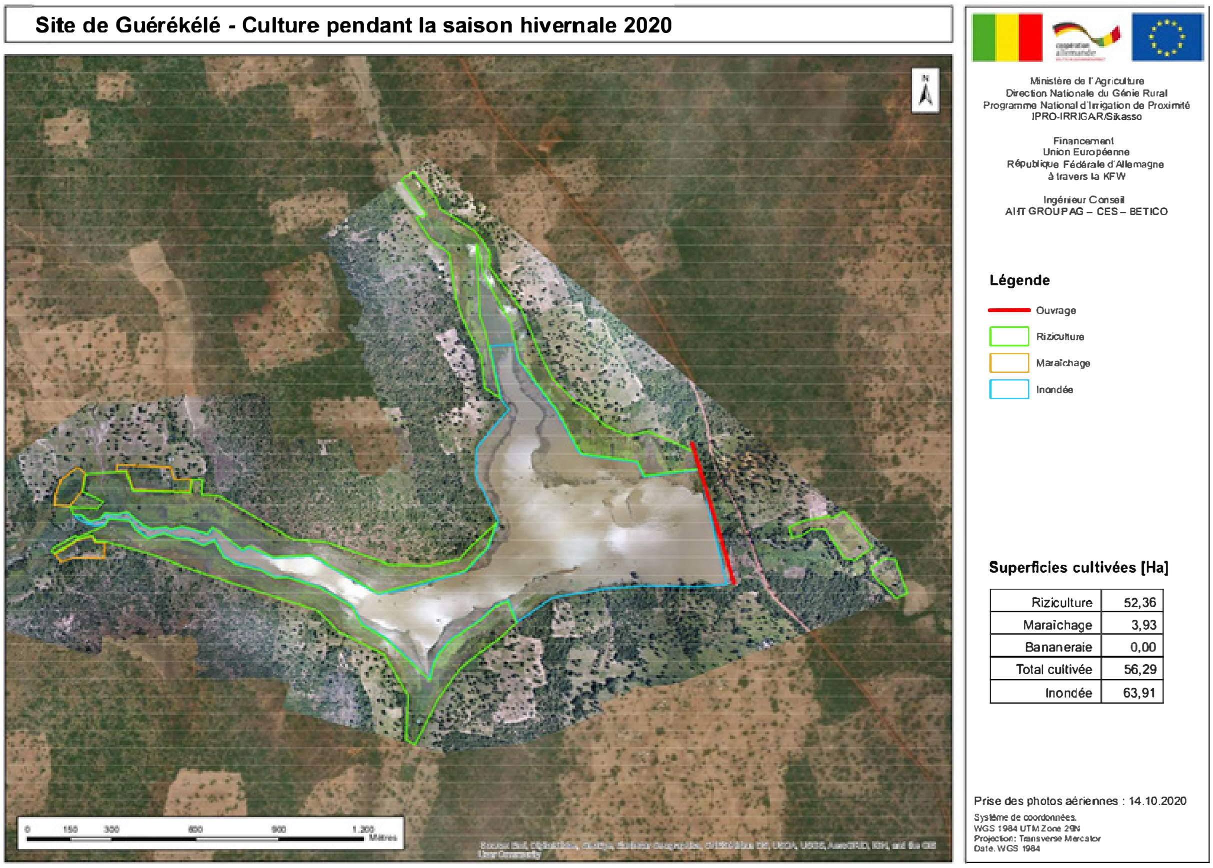
7. ANNEX 1: PROJECT LOCATIONS AND DATA

Figure A1.1 Locations of all project site polygons for Mali Nord



Source: authors' own figure

Figure A1.2 Example of Sikasso project site PDF contents



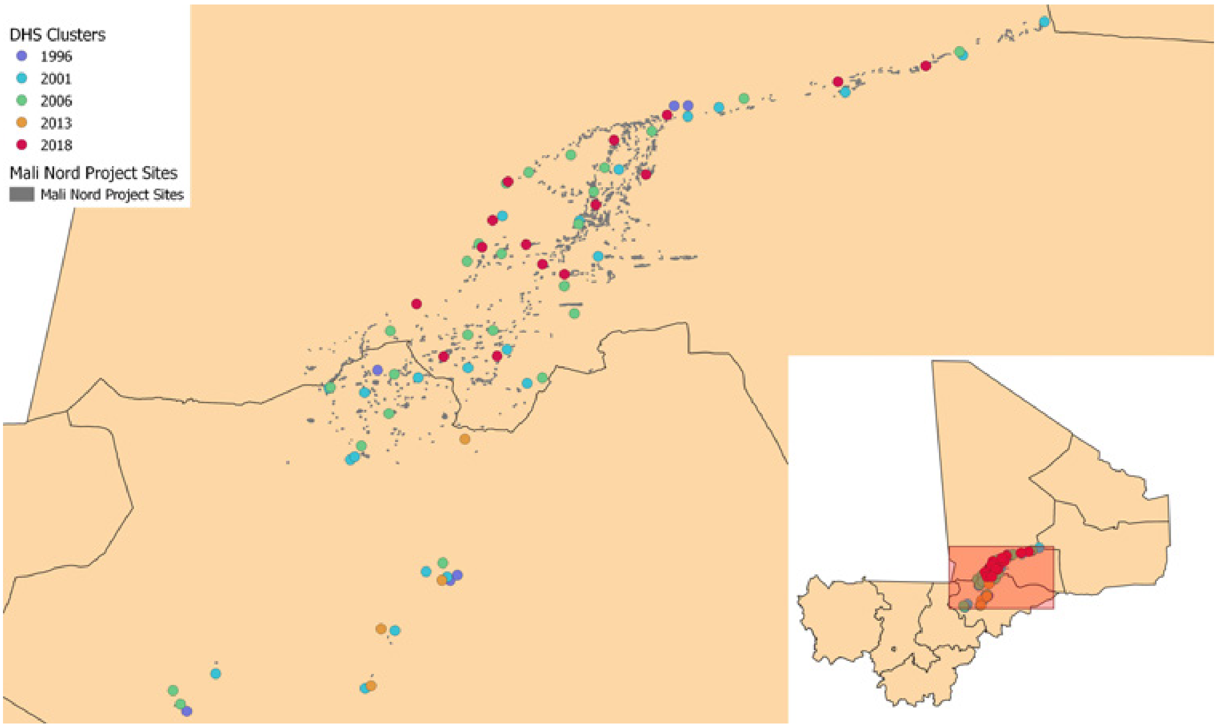
Superficies cultivées [Ha]

Riziculture	52,36
Maraîchage	3,93
Bananeraie	0,00
Total cultivée	56,29
Inondée	63,91

Source: KfW

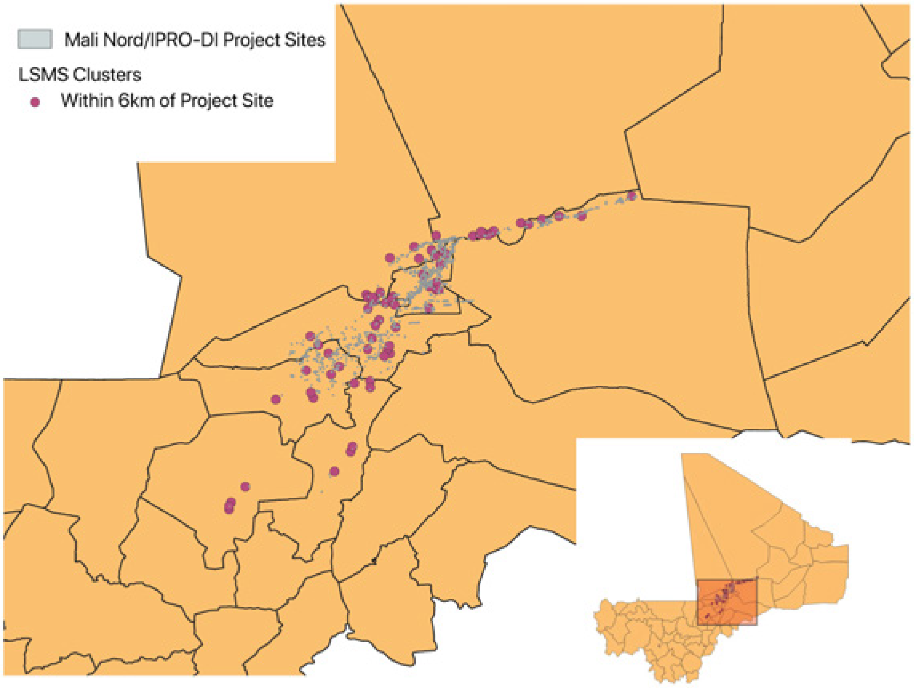
Note: Example PDF record of project site that was georeferenced and traced to extract geospatial features..

Figure A1.3 DHS cluster locations within 6 km of IPRODI/Mali Nord project sites



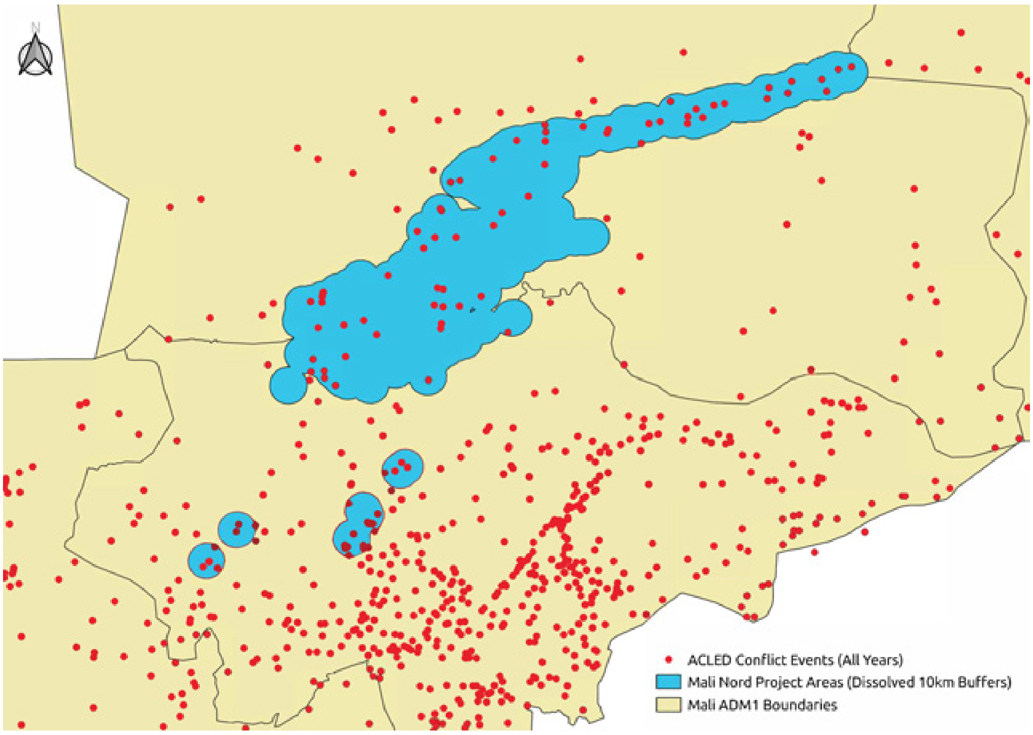
Source: authors' own figure

Figure A1.4 LSMS cluster locations within 6 km of IPRODI/Mali Nord project sites



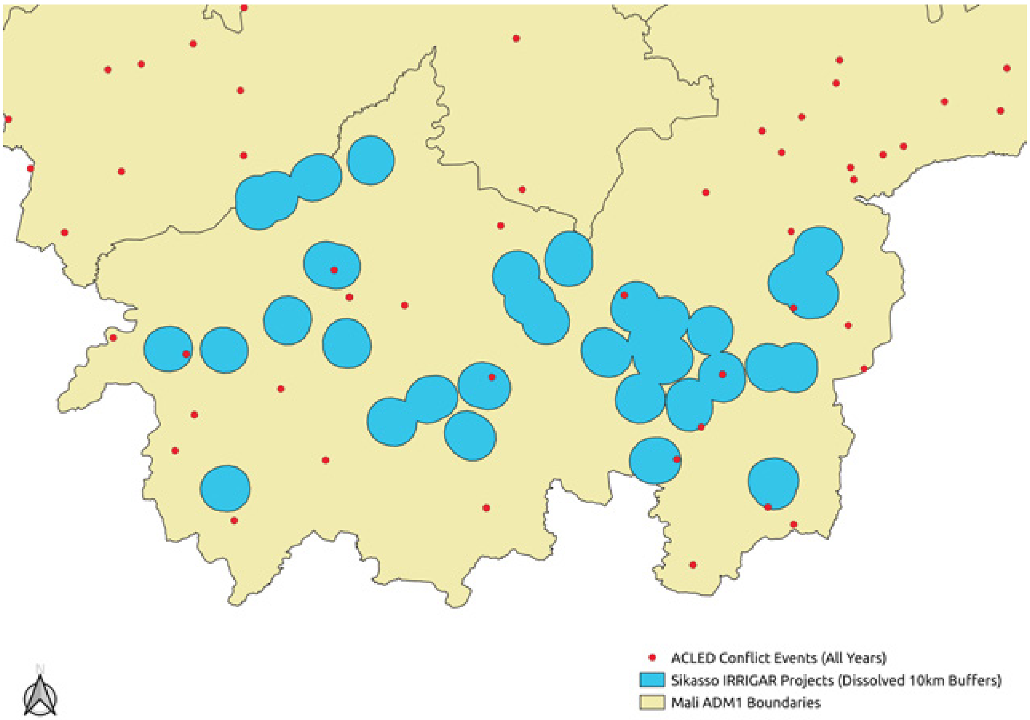
Source: authors' own figure

Figure A1.5 ACLED event locations around dissolved 10 km buffers of Mali Nord project sites



Source: authors' own figure

Figure A1.6 ACLED event locations around dissolved 10 km buffers of Sikasso project sites



Source: authors' own figure

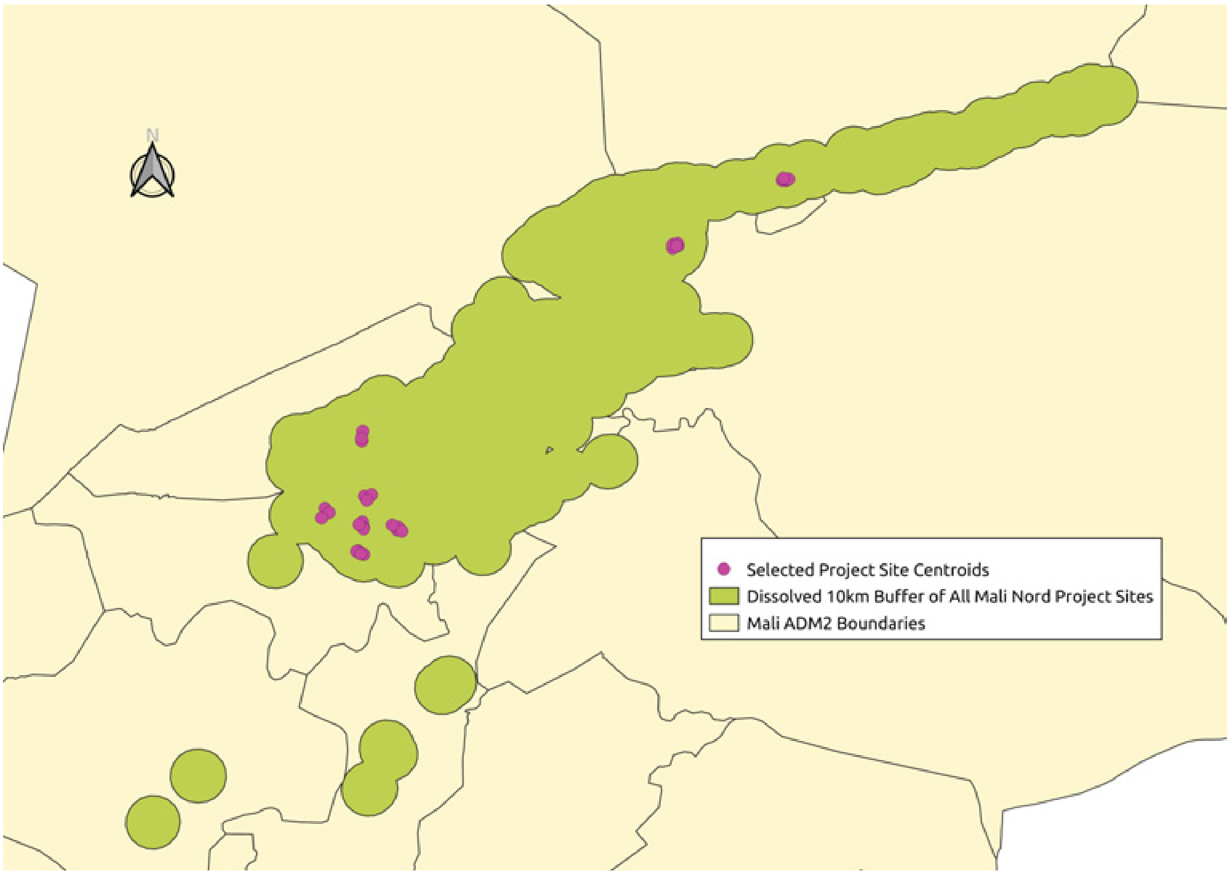
Table A1.1 Very high-resolution satellite imagery: key characteristics used in visual interpretation

Satellite	Sensor	Number of bands	Spatial resolution (m)	Archive from
IKONOS	MS and PAN	4 and 1	4-m and 1-m	1999
QuickBird	MS and PAN	4 and 1	2.4-m and 0.6-m	2001
WorldView-1	PAN	1	0.5-m	2007
WorldView-2	MS and PAN	8 and 1	1.84-m and 0.5-m	2009
WorldView-3	MS and PAN	8 and 1	1.24-m and 0.31-m	2014
Pleiades	MS and PAN	4 and 1	2.8-m and 0.5-m	2012
KOMPSAT-2	MS and PAN	4 and 1	4-m and 1-m	2006
KOMPSAT-3	MS and PAN	4 and 1	2.8-m and 0.7-m	2012
Gaofen	MS and PAN	4 and 1	3.2-m and .08-m	2014
GeoEye	MS and PAN	4 and 1	2-m and 0.5-m	2008
Superview	MS and PAN	4 and 1	2-m and 0.5-m	2018

Table A1.2 Selected project site clusters

Project site clusters	Region	Irrigation start year	Area (km^2)
Aglal	Tombouctou	2015	0.591
Ambiri	Mopti	2015	0.455
Babagoungou	Mopti	2016	0.272
Chirfina	Mopti	2015	0.313
Firobe	Mopti	2015	0.337
Sébi Femmes	Mopti	2017	0.260
Singama	Mopti	2016	0.051
Tissikinen	Tombouctou	2017	0.123

Figure A1.7 **Overview of project site clusters selected for VHR analysis**



Source: authors' own figure

Table A1.3 ACLED conflict data

Group	Actors
state	Government of Mali (2013–2020) Military Forces of Mali (2002–2012) Military Forces of Mali (2012–2013) Military Forces of Mali (2013–2020)” Military Forces of Mali (2013–2020) Operational Coordination Mechanism Military Forces of Mali (2020–) Police Forces of Mali (1992–2002) Police Forces of Mali (2002–2012) Police Forces of Mali (2012–2013) Police Forces of Mali (2013–2020) Police Forces of Mali (2013–2020) Gendarmerie Police Forces of Mali (2013–2020) Prison Guards Police Forces of Mali (2020–) Gendarmerie
external	Military Forces of Mauritania (2009–) Military Forces of France (2017–) Military Forces of France (2012–2017) MINUSMA: United Nations Multidimensional Integrated Stabilization Mission in Mali (2013–) Military Forces of Niger (2011–2021) Military Forces of Chad (1990–2021) G5S: G5 Sahel Force (2017–) Military Forces of Algeria (1999–)
jihadist	Islamic State (Greater Sahara) JNIM: Group for Support of Islam and Muslims MUJAO: Movement for Unity and Jihad in West Africa Islamic State (West Africa) - Greater Sahara Faction AQIM: Al Qaeda in the Islamic Maghreb JNIM: Group for Support of Islam and Muslims and/or Islamic State (West Africa) - Greater Sahara Faction Ansar Dine
militia	Militia (Students) Militia (Miners) Militia (Pro-Government) Dozo Militia Islamist Militia (Mali) Tourmouz Clan Militia (Mali) Shiite Muslim Militia (Mali) Dire Communal Militia (Mali) Unidentified Communal Militia (Mali) Bananso Communal Militia (Mali)

	Dozo Communal Militia (Mali) Arab Ethnic Militia (Mali) Bambara Ethnic Militia (Mali) Dogon Ethnic Militia (Mali) Ganda Izo Ethnic Militia (Mali) Tuareg Ethnic Militia (Mali) Fulani Ethnic Militia (Mali) Soninke Ethnic Militia (Mali) Dawsahak Ethnic Militia (Mali) Gandakoy Ethnic Militia (Mali) Songhai Ethnic Militia (Mali)
groups	Platform of June 14th 2014 movements Ganda Izo Ansaroul Islam Katiba Macina Katiba Serma Alliance for the Salvation of the Sahel Al Mourabitoune Battalion Dan Na Ambassagou MAA: Arab Movement of the Azawad (CMA) CJA: Congress for Justice in Azawad MAA: Arab Movement of the Azawad (Platform) MSA: Movement for Azawad Salvation CMA: Coordination of Movements of the Azawad GATIA: Imghad Tuareg and Allies Self-Defense Group MAA: Arab Movement of the Azawad ADC: Democratic Alliance of 23rd May for Change GSPC: Salafist Group for Call and Combat MNLA: National Movement for the Liberation of Azawad ATNMC: North Mali Tuareg Alliance for Change GMA: Mourabitounes Group of Azawad HCUA: High Council for the Unity of Azawad
other	Civilians (Mali) Protesters (Mali) Rioters (Mali) Unidentified Armed Group (Mali) Mutiny of Military Forces of Mali (2002-2012) Mutiny of Military Forces of Mali (2013-2020)

This Annex provides a comparison of the ACLED dataset used to evaluate project impacts on conflict in this paper with alternative sources of conflict data. In addition to ACLED, the following conflict datasets were evaluated for use in this paper:

- SCAD – Social Conflict Analysis Database
- UCDP GED – Uppsala Conflict Data Program Georeferenced Event Dataset

- GTD – Global Terrorism Database
- WARICC – Water-related Intrastate Conflict and Cooperation (Böhmelt et al., 2014)
- Mopti land conflict court data (Benjaminsen et al., 2012)

ACLED includes a broad range of event types such as battles, violence against civilians, explosions, riots, and protests which can be further refined based on actors involved (state forces, rebels, civilians etc.), type of interactions (i.e. pairing of actors involved) and fatalities. ACLED contains nearly 5 000 events between 1997 and 2021 in Mali.

UCDP-GED focuses on organised violence and attempts to geocode events down to the individual village and day. It includes state-based conflict, non-state conflict, and one-sided violence, with details on actors involved on each side, and considerable details on the precision with which event information was recorded. UCDP-GED contains nearly 1 000 events total occurring between 1990 and 2019 in Mali.

SCAD is focused on social conflict events, which are not as well tracked in other conflict datasets. The dataset contains considerable detail specific to social conflict event types (e.g. topic of protest or strike, domains of groups involved). While details on events as a whole are well documented, individual location details (e.g. specific details of protest at one location that is part of a series of protests coded as a single event) are limited. The dataset has coverage from 1991 to 2017, yet the majority of records are from the past decade. SCAD contains over 500 recorded events in Mali.

GTD provides information on terrorist attacks around the world since 1970, and contains over 800 events in Mali. The open source dataset provides a range of details on events including date, location, actors, casualties and more.

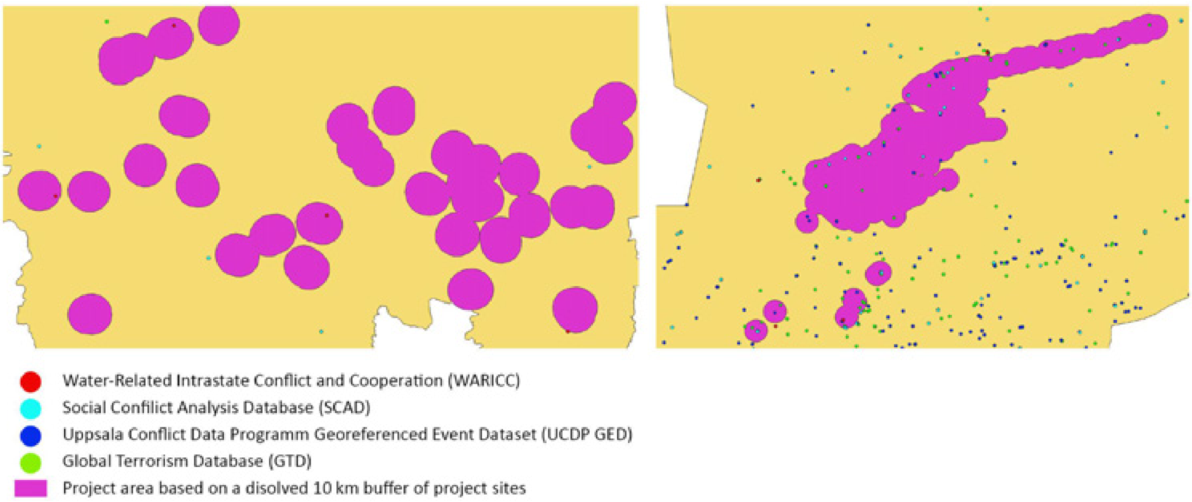
WARICC focuses on both conflict and cooperation events related to water. The dataset contains fewer than 100 events in Mali between 1997 and 2009.

The Mopti land conflict court data contain 143 records prior to 2009.

Considerable overlap exists between the datasets, but many records unique to each dataset do exist. ACLED has been shown to have the greatest amount of unique events due to its breadth of coverage of event type, yet SCAD has many unique social conflict events (protests, riots, etc) and UCDP-GED has unique organised armed conflict events (Dunford, 2019). Across the datasets, spatiotemporal precision can vary, depending on available information and context for the events. For example, while some discrete events may be well recorded at a given time and place, others take place over broader periods and without exact locations (e.g. an entire administrative zone).

To explore the alternative datasets we produced maps using a 10-km buffer around project site polygons in Sikasso (see Figure A1.8, left in Annex 2) and Mali Nord (see Figure A1.8, right). Data from the WARICC, SCAD, UCDP GED and GTD datasets are overlaid.

Figure A1.8 Conflict data



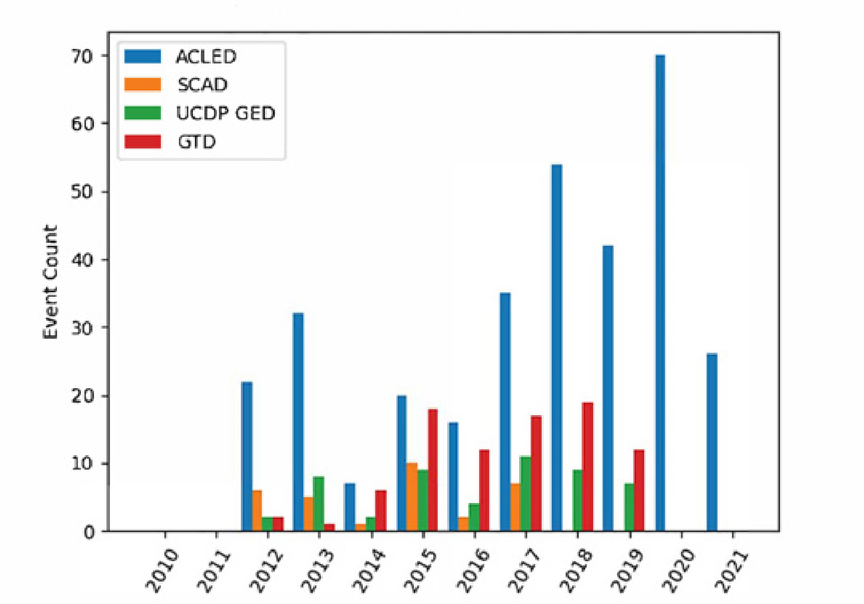
Source: authors' own figure

Note: The figure shows conflict events from different data sources around project clusters in Sikasso (left) and Mali Nord (right).

The WARICC data contained few events in both the Sikasso and Mali Nord regions (see red points in the maps in Figure A1.8 in Annex 2), and all were minor cooperative events that did not involve conflict. The Mopti land conflict court data provides locations based only on communes, and the majority of commune names in the dataset could not be linked to current commune boundaries in the Mali Nord or Sikasso regions. In the Sikasso region, no events from SCAD, UCDP GED, or GTD occurred within a 10-km buffer of the project sites.

In the Mali Nord region, a number of events from SCAD (32), UCDP GED (66), and GTD (95) do exist within the buffers. For comparison, 324 events from ACLED exist within the same buffers. A temporal distribution of events for each of these datasets is included Figure A1.9 in Annex 2. The temporal distribution shows that there are fairly few events per year for the alternate datasets (fewer than 10 on average) compared to ACLED.

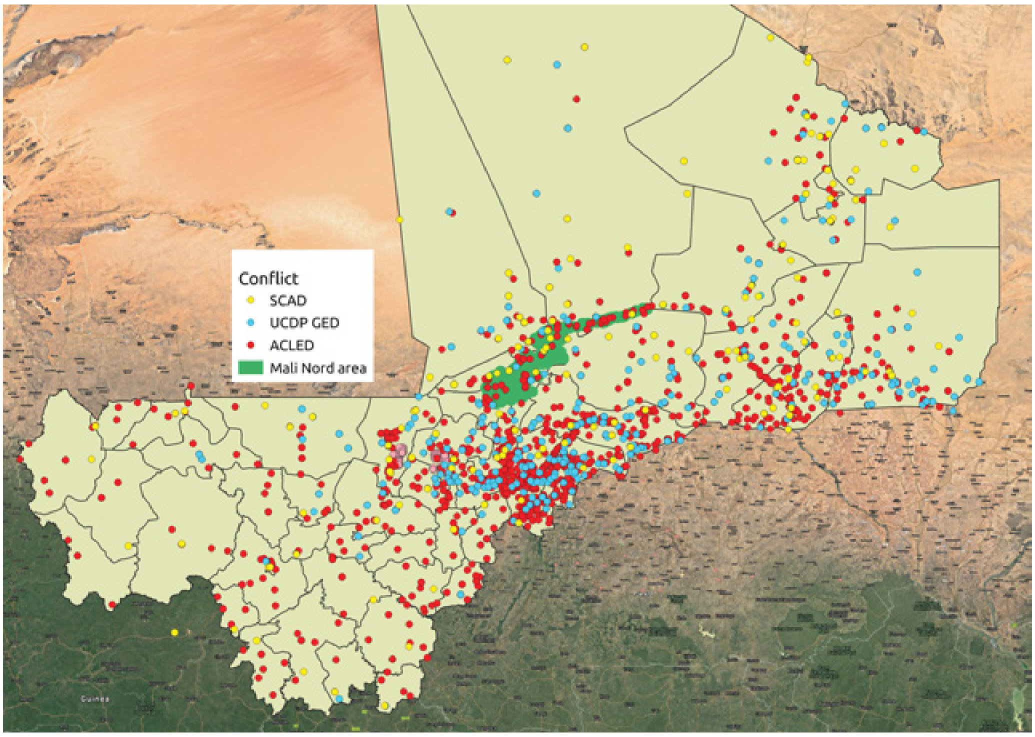
Figure A1.9 Conflict data temporal distribution



Source: authors' own figure

Given that the Mali War began in 2012, the general lack of earlier conflict data may be in line with actual trends, but could reflect gaps in historical data coverage. A map of all conflict events in Mali for any year from ACLED, UCDP-GED, and SCAD – the three most numerous and commonly used datasets – is provided in Figure A1.9 for context.

Figure A1.10 Conflict data across Mali



Source: authors' own figure

The map shows conflict data from different sources from 1999-2021.

8. ANNEX 2: ADDITIONAL RESULTS

Table A2.1 Agricultural production for IPRODI/Mali Nord pump-based irrigation

	(1)	(2)	(3)	(4)	(5)
	NDWI	**NDVI mean (pre-rainy season)**	**NDVI mean (pre-rainy season)**	**NDVI mean (growing season)**	**NDVI mean (growing season)**
Years-to-treatment <-10	6.33e-07	0.00365*	0.00307	0.0203**	0.0278***
	(0.00204)	(0.00191)	(0.00209)	(0.00856)	(0.00733)
Years-to-treatment -10 to -5	0.000302	0.00138	0.00131	0.0119**	0.0161***
	(0.00158)	(0.00172)	(0.00172)	(0.00510)	(0.00436)
Years-to-treatment -5 to -1	0.000264	0.000129	0.000441	0.000436	0.00222
	(0.00114)	(0.000952)	(0.00101)	(0.00396)	(0.00385)
Years-to-treatment 0 to 1	0.00244*	-0.00191*	-0.00149	0.00944*	0.00851
	(0.00118)	(0.00106)	(0.00111)	(0.00547)	(0.00540)
Years-to-treatment 1 to 5	0.00477***	0.00451***	0.00450***	0.0393***	0.0379***
	(0.00150)	(0.00101)	(0.00106)	(0.00764)	(0.00785)
Years-to-treatment 5 to 10	0.00517**	0.00527***	0.00580***	0.0357***	0.0314***
	(0.00186)	(0.00139)	(0.00134)	(0.00793)	(0.00655)
Years-to-treatment 10+	0.00447*	0.00460**	0.00394*	0.0252**	0.0214**
	(0.00252)	(0.00201)	(0.00212)	(0.00916)	(0.00871)
Observations	16,409	16,388	16,410	15,195	15,195
R-squared	0.595	0.773	0.756	0.594	0.602
Polygon FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Region-Year FEs	Y	N	Y	N	Y
Weather controls	Y	Y	Y	Y	Y

Source: authors' own table

*The reference (base) group is years-to-treatment = -1 (i.e. the baseline year immediately before the completion of the irrigation). Standard errors are clustered two ways by year and grid-cell. * p<0.1, ** p<0.05, *** p<0.01.*

Table A2.2 Upstream sites mediate downstream impacts

	(1)	(2)
	NDVI mean (growing season)	NDVI mean (growing season)
Years-to-treatment <-10	0.0286**	
	(0.0120)	
Years-to-treatment -10 to -5	0.0199**	
	(0.00815)	
Years-to-treatment -5 to -1	0.00391	
	(0.00429)	
Years-to-treatment 0 to 1	0.0187	
	(0.0114)	
Years-to-treatment 1 to 5	0.0624***	
	(0.0116)	
Years-to-treatment 5 to 10	0.0478***	
	(0.0128)	
Years-to-treatment 10+	0.0402**	
	(0.0185)	
Upstream active project sites (binned)	0.000546**	
	(0.000218)	
Years-to-treatment <-10 X Upstream active project sites (binned)	0.000168	
	(0.000265)	
Years-to-treatment -10 to -5 X Upstream active project sites (binned)	-4.68e-05	
	(0.000227)	
Years-to-treatment -5 to -1 X Upstream active project sites (binned)	-1.48e-05	
	(8.79e-05)	
Years-to-treatment 0 to 1 X Upstream active project sites (binned)	-0.000222	
	(0.000146)	
Years-to-treatment 1 to 5 X Upstream active project sites (binned)	-0.000496***	
	(0.000135)	
Years-to-treatment 5 to 10 X Upstream active project sites (binned)	-0.000317*	
	(0.000171)	
Years-to-treatment 10+ X Upstream active project sites (binned)	-0.000338	
	(0.000233)	
why		0.0154
		(0.0281)
Upstream active project sites 1 to <10		-0.00285
		(0.00661)
Upstream active project sites 10 to <50		0.00510
		(0.0113)
Upstream active project sites 50 to <100		0.0166

		(0.0119)
Upstream active project sites >100		0.0144
		(0.0191)
Post-treatment X Upstream active project sites 1 to <10		0.0264
		(0.0249)
Post-treatment X Upstream active project sites 10 to <50		0.0178
		(0.0274)
Post-treatment X Upstream active project sites 50 to <100		0.0134
		(0.0274)
Post-treatment X Upstream active project sites >100		0.0143
		(0.0290)
Observations	15,195	15,195
R-squared	0.603	0.598
Polygon FEs	Y	Y
Year FEs	Y	Y
Region-Year FEs	Y	Y
Weather controls	Y	Y

Source: authors' own table

*The reference (base) group is years-to-treatment = -1 (i.e. the baseline year immediately before the completion of the irrigation). Standard errors are clustered two ways by year and grid-cell. * p<0.1, ** p<0.05, *** p<0.01.*

Table A2.3 Effect of irrigation on agricultural production, conditional on conflict

	(1)	(2)	(3)
	NDWI	**NDVI mean (pre-rainy season)**	**NDVI mean (growing season)**
Years-to-treatment <-10	-0.00204	0.00727**	0.0324**
	(0.00400)	(0.00305)	(0.0116)
Years-to-treatment -10 to -5	-0.00146	0.00533***	0.0125**
	(0.00203)	(0.000976)	(0.00417)
Years-to-treatment -5 to -1	0.00351	-0.00139	-0.00357
	(0.00266)	(0.00142)	(0.00708)
Years-to-treatment 0 to 1	0.00909***	0.00162	0.00645
	(0.00177)	(0.00166)	(0.0120)
Years-to-treatment 1 to 5	0.0121***	-0.000734	0.0191
	(0.00242)	(0.00389)	(0.0207)
Conflict 2012-2014 X Years-to-treatment <-10	-0.0103**	-0.00701	0.0234*
	(0.00414)	(0.00596)	(0.0117)
Conflict 2012-2014 X Years-to-treatment -10 to -5	-0.00602	-0.00574*	0.00269
	(0.00401)	(0.00273)	(0.0110)
Conflict 2012-2014 X Years-to-treatment -5 to -1	-0.00428	-0.00280	0.00434
	(0.00459)	(0.00399)	(0.00661)
Conflict 2012-2014 X Years-to-treatment 0 to 1	0.000870	-0.000786	0.0196
	(0.00474)	(0.00254)	(0.0130)
Conflict 2012-2014 X Years-to-treatment 1 to 5	-0.00143	-0.00758	0.0198
	(0.00706)	(0.00472)	(0.0297)
Observations	2,485	2,476	2,473
R-squared	0.621	0.837	0.665
Polygon FEs	Y	Y	Y
Year FEs	Y	Y	Y
Region-Year FEs	Y	Y	Y
Weather controls	Y	Y	Y

Source: authors' own table

*Note: The reference (base) group is years-to-treatment = -1 (i.e. the baseline year immediately before the completion of the irrigation). Standard errors are clustered two ways by year and grid-cell. * p<0.1, ** p<0.05, *** p<0.01.*

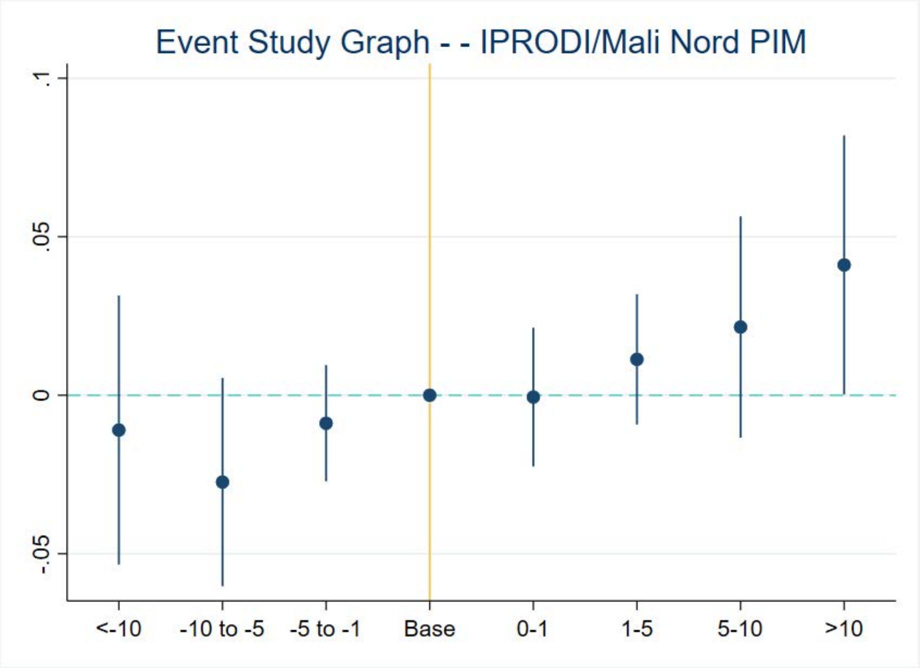
Table A2.4 Agricultural production – IPRODI/Mali Nord mares

	(1)	(2)	(3)	(4)	(5)
	NDWI	NDVI mean (pre-rainy season)	NDVI mean (pre-rainy season)	NDVI mean (growing season)	NDVI mean (growing season)
Years-to-treatment <-10		0.0112	0.0104	0.0139	-0.0110
		(0.0160)	(0.0179)	(0.0185)	(0.0203)
Years-to-treatment -10 to -5	-0.00327	0.00886	-0.00212	-0.0143	-0.0274*
	(0.0155)	(0.0129)	(0.0105)	(0.0168)	(0.0157)
Years-to-treatment -5 to -1	0.00456	0.00421	-0.00158	-0.00415	-0.00884
	(0.00513)	(0.00614)	(0.00366)	(0.00894)	(0.00879)
Years-to-treatment 0 to 1	0.0145	0.0119	0.00816	0.000970	-0.000576
	(0.0122)	(0.00759)	(0.00595)	(0.0113)	(0.0105)
Years-to-treatment 1 to 5	0.00326	0.0110*	0.0101*	0.00747	0.0113
	(0.00865)	(0.00619)	(0.00502)	(0.00831)	(0.00986)
Years-to-treatment 5 to 10	0.0106	0.0118	0.00917	0.00882	0.0215
	(0.0119)	(0.00748)	(0.00732)	(0.0128)	(0.0167)
Years-to-treatment 10+	0.00842	0.0186**	0.0138	0.0270	0.0411**
	(0.0138)	(0.00693)	(0.00815)	(0.0159)	(0.0196)
Observations	2,291	2,925	2,922	2,739	2,738
R-squared	0.711	0.765	0.793	0.583	0.643
Polygon FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Region-Year FEs	Y	N	Y	N	Y
Weather controls	Y	Y	Y	Y	Y

Source: authors' own table

*Note: The reference (base) group is years-to-treatment = -1 (i.e. the baseline year immediately before the completion of the irrigation). Standard errors are clustered two ways by year and grid-cell. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.1 Effect of flooded areas/mare on agricultural production in IPRODI/Mali Nord



Source: authors' own figure

Note: The figure shows the effect of flooded areas/mares (treatment) on agricultural production (proxied by NDVI) in IPRODI/Mali Nord at different year intervals, relative to the year before treatment began (Base). Each point represents the mean difference in the outcome between the year interval and the base year; each line represents the confidence interval for each point estimate. The figure is based on Table A2.4 column 5.

Table A2.5 Agricultural production – Sikasso

	(1)	(2)	(3)	(4)	(6)
	NDWI	NDVI mean (growing season)	NDVI mean (growing season)	NDVI mean (growing season)	NDVI mean (growing season)
Type		Flooded	Market Garden	Rice	All Other
Years-to-treatment <-10	-0.0137	0.0513	-0.0232	-0.0165	0.00614
	(0.0135)	(0.0459)	(0.0245)	(0.0266)	(0.0520)
Years-to-treatment -10 to -5	-0.00905	0.0457	-0.0261	0.00362	0.00346
	(0.0103)	(0.0514)	(0.0172)	(0.0210)	(0.0490)
Years-to-treatment -5 to -1	-0.0109	0.0241	-0.0154*	0.0115	-0.000961
	(0.00823)	(0.0261)	(0.00794)	(0.0121)	(0.0400)
Years-to-treatment 0 to 1	-0.000430	-0.0451***	-0.0746***	-0.0364***	-0.0632
	(0.00272)	(0.0123)	(0.0151)	(0.00788)	(0.0436)
Years-to-treatment 1+	0.0156***	-0.0964***	-0.0521***	-0.0519***	-0.0933*
	(0.00505)	(0.0237)	(0.0139)	(0.0140)	(0.0539)
Observations	12,304	959	2,313	3,351	460
R-squared	0.767	0.589	0.560	0.581	0.812
Polygon Fes	Y	Y	Y	Y	Y
Year Fes	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
Cercle-Year FEs	Y	Y	Y	Y	Y

Source: authors' own table

*Note: The reference (base) group is years-to-treatment = -1 (i.e. the baseline year immediately before the completion of the irrigation). Standard errors are clustered two ways by year and grid-cell. * p<0.1, ** p<0.05, *** p<0.01.*

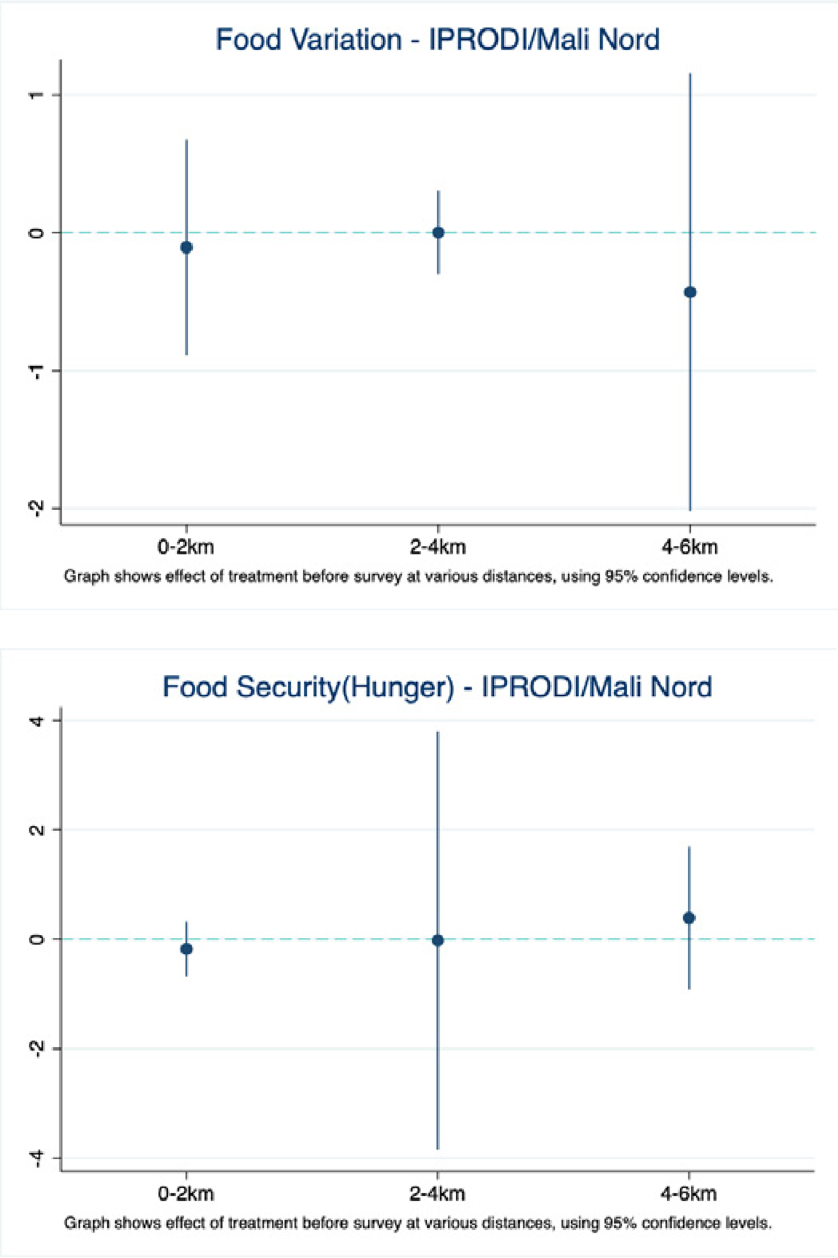
Table A2.6 Effect of treatment on food security – IPRODI/Mali Nord

	(1)	**(2)**
	Cannot Vary Food	**Hunger**
Treated Before Survey (0-2km)	-0.107	-0.180
	(0.0615)	(0.0394)
Treated Before Survey (2-4km)	0.000983	-0.0205
	(0.0239)	(0.302)
Treated Before Survey (4-6km)	-0.431	0.392
	(0.125)	(0.102)
Observations	241	262
R-squared	0.367	0.161
Cercle FEs	Y	Y
Wave FEs	Y	Y

Source: authors' own table

*Note: Cannot vary food is a binary variable which indicates if someone in the household answered "Often true" to the statement "We cannot vary what we eat, and we almost always eat the same thing", about the last 12 months. Hunger is a binary variable which indicates if someone replied "yes" to the statement, "In the past 12 months, have you ever been hungry and not eaten because there was not enough food or not enough money?" Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.2 Effect of irrigation on food security



Source: authors' own figure

Note: This figure shows the estimated treatment effect on the inability to vary food (upper figure) and in the occurrence of hunger/the insufficiency of food (lower figure) at different distance bands from the project location. Each point represents the estimated treatment effect on the outcome in each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.6.

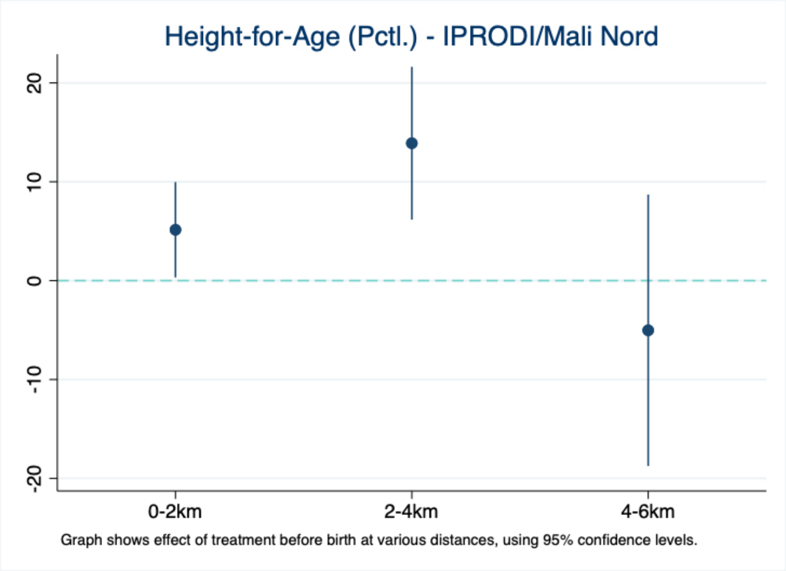
Table A2.7 Effect of treatment before birth on child stunting – IPRODI/Mali Nord

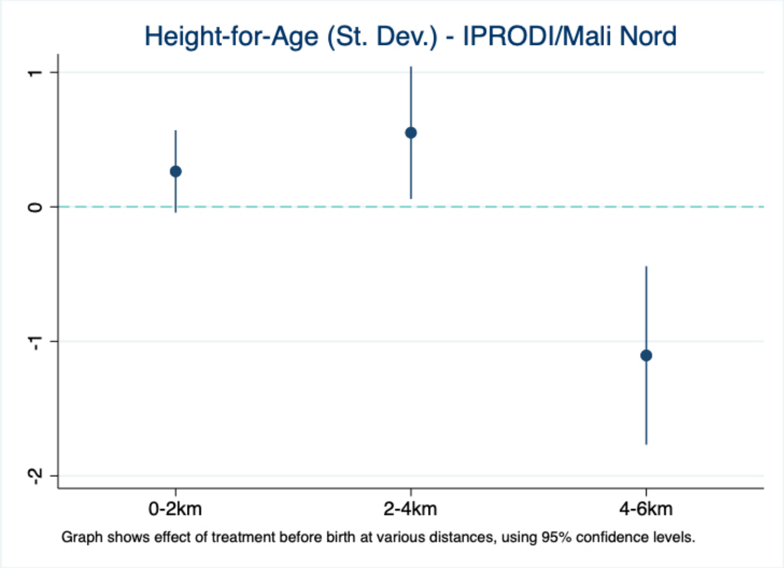
	(1)	**(2)**	**(3)**
	Height-for-Age (Percentile)	**Height-for-Age (Std. Dev.)**	**Height-for-Age (% of Median)**
Treated Before Birth (0-2km)	5.145**	0.264*	1.090*
	(2.337)	(0.148)	(0.588)
Treated Before Birth (2-4km)	13.90***	0.551**	2.135**
	(3.745)	(0.239)	(0.949)
Treated Before Birth (4-6km)	-5.023	-1.105***	-4.490***
	(6.651)	(0.321)	(1.269)
Observations	1,603	1,603	1,603
R-squared	0.084	0.107	0.108
Region FEs	Y	Y	Y
Cohort FEs	Y	Y	Y

Source: authors' own table

*Note: Height-for-age is a measure of stunting relative to other children of the same age. Height-for-age is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.3 **Effect of treatment before birth on child stunting**





Source: authors´ own figure

Note: This figure shows the estimated treatment effect on child stunting (height-for-age) at different distance bands from the project location. Treatment is considered nearby project completion prior to birth. Height-for-age is measured as percentile in the upper graph and as standard deviations from the reference median in the lower graph. Each point represents in the estimated treatment effect on the outcome in each distance band; each line represents the confidence interval for each point estimate. The figures are based on Table A2.7 (upper graph on column 1 and graph below on column 2).

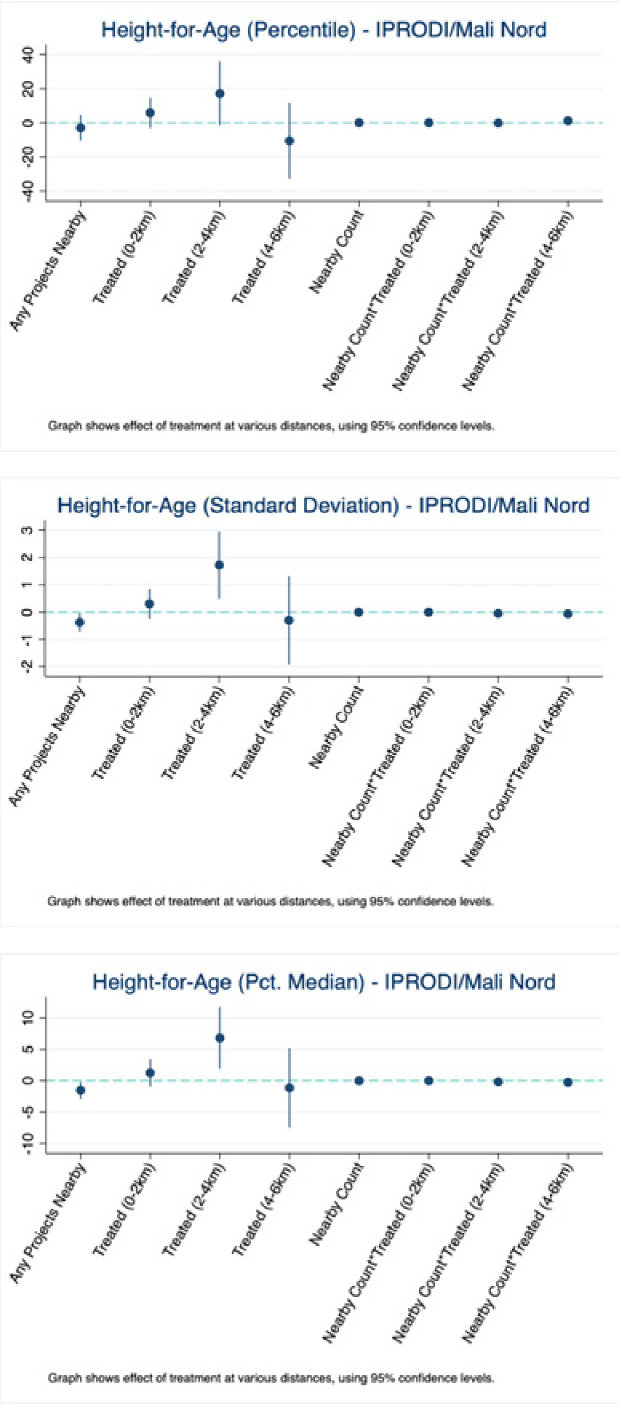
Table A2.8 Effect of treatment before birth on child stunting with nearby project controls – IPRODI/Mali Nord

	(1) Height-for-Age (Percentile)	(2) Height-for-Age (St. Dev.)	(3) Height-for-Age (% of Median)
Nearby Any	-2.903	-0.373**	-1.530**
	(3.593)	(0.160)	(0.641)
Nearby Count	-0.0119	-0.000962	-0.00473
	(0.108)	(0.00516)	(0.0210)
Max Nearby Count	0.0219	0.00194	0.00804
	(0.0249)	(0.00130)	(0.00534)
Treated Before Birth (0-2km)	5.837	0.302	1.235
	(4.334)	(0.266)	(1.059)
Treated Before Birth (2-4km)	17.16*	1.718***	6.819***
	(8.972)	(0.589)	(2.367)
Treated Before Birth (4-6km)	-10.56	-0.300	-1.139
	(10.49)	(0.770)	(3.031)
Nearby Count*Treated Before Birth (0-2km)	-0.00982	-0.000476	-0.00140
	(0.0825)	(0.00456)	(0.0185)
Nearby Count*Treated Before Birth (2-4km)	-0.186	-0.0487**	-0.195**
	(0.280)	(0.0176)	(0.0712)
Nearby Count*Treated Before Birth (4-6km)	1.213	-0.0637	-0.272
	(0.931)	(0.0656)	(0.259)
Observations	1,321	1,321	1,321
R-squared	0.089	0.119	0.120
Region FEs	Y	Y	Y
Cohort FEs	Y	Y	Y

Source: authors' own table

*Note: Height-for-age is a measure of stunting relative to other children of the same age. Height-for-age is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of reference median in column 3. Nearby Any is a binary variable indicating whether there are any project sites that have been completed within 20 km, excluding the nearest. Nearby Count is a count of projects within 20 km that have been completed, excluding the nearest. Max Nearby Count is the number of projects within 20 km that have been completed by 2020. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.4 Effect of irrigation before birth on child stunting with nearby project controls



Source: authors´ own figure

Note: This figure shows the estimated treatment effect on child stunting (height-for-age) at different distance bands from the project location. It also shows the moderating effect of the number of other treated areas nearby on this treatment effect. Treatment is considered nearby project completion prior to birth. Height-for-age is measured as percentile in the upper graph, as standard deviations from the reference median in the figure in the middle, and as percentage of reference median in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure s are based on Table A2.8.

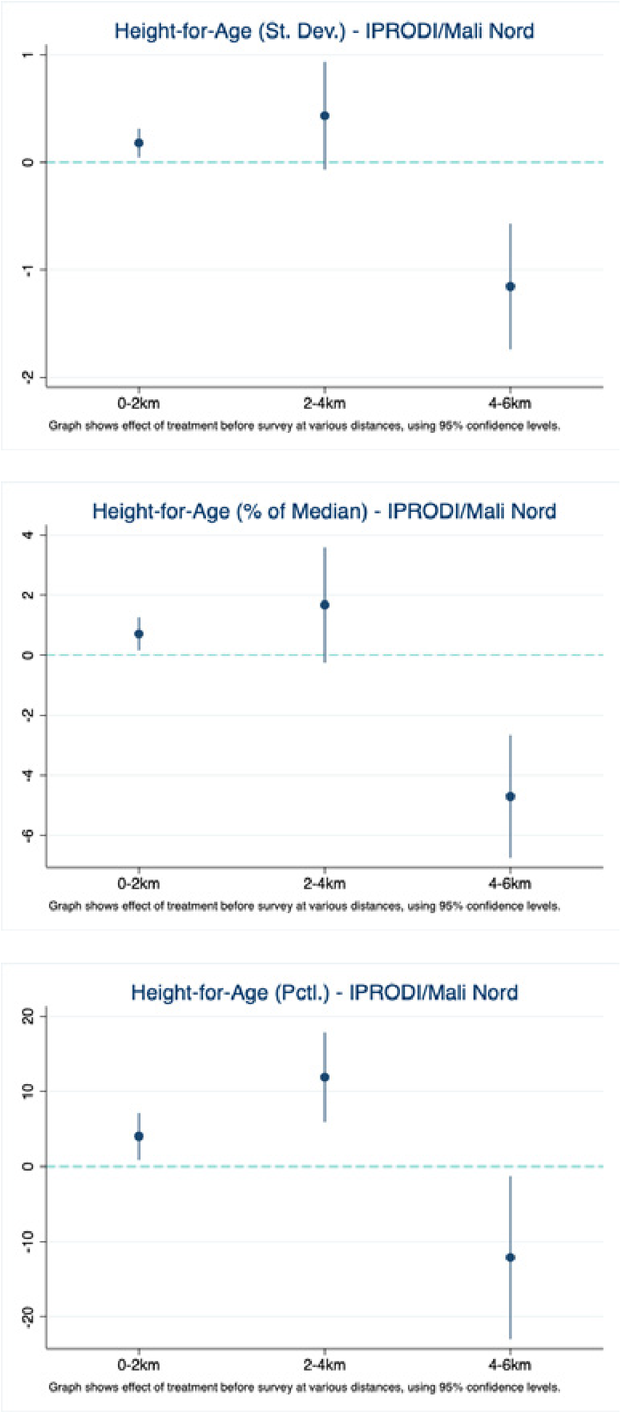
Table A2.9 Effect of treatment before survey on child stunting – IPRODI/Mali Nord

	(1)	(2)	(3)
	Height-for-Age (Percentile)	**Height-for-Age (Std. Dev.)**	**Height-for-Age (% of Median)**
Treated Before Survey (0-2km)	4.022**	0.177**	0.714**
	(1.134)	(0.0483)	(0.200)
Treated Before Survey (2-4km)	11.88***	0.431*	1.673*
	(2.159)	(0.180)	(0.690)
Treated Before Survey (4-6km)	-12.12**	-1.155***	-4.698***
	(3.906)	(0.211)	(0.734)
Observations	1,603	1,603	1,603
R-squared	0.020	0.034	0.035
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Height-for-age is a measure of stunting relative to other children of the same age. Height-for-age is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01*

Figure A2.5 Effect of treatment before survey on child stunting



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child stunting (height-for-age) at different distance bands from the project location. Treatment is considered nearby project completion prior to the survey. Height-for-age is measured as percentile in the upper graph, as standard deviations from the reference median in the middle graph, and as percentage of reference median in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figures are based on Table A2.9.

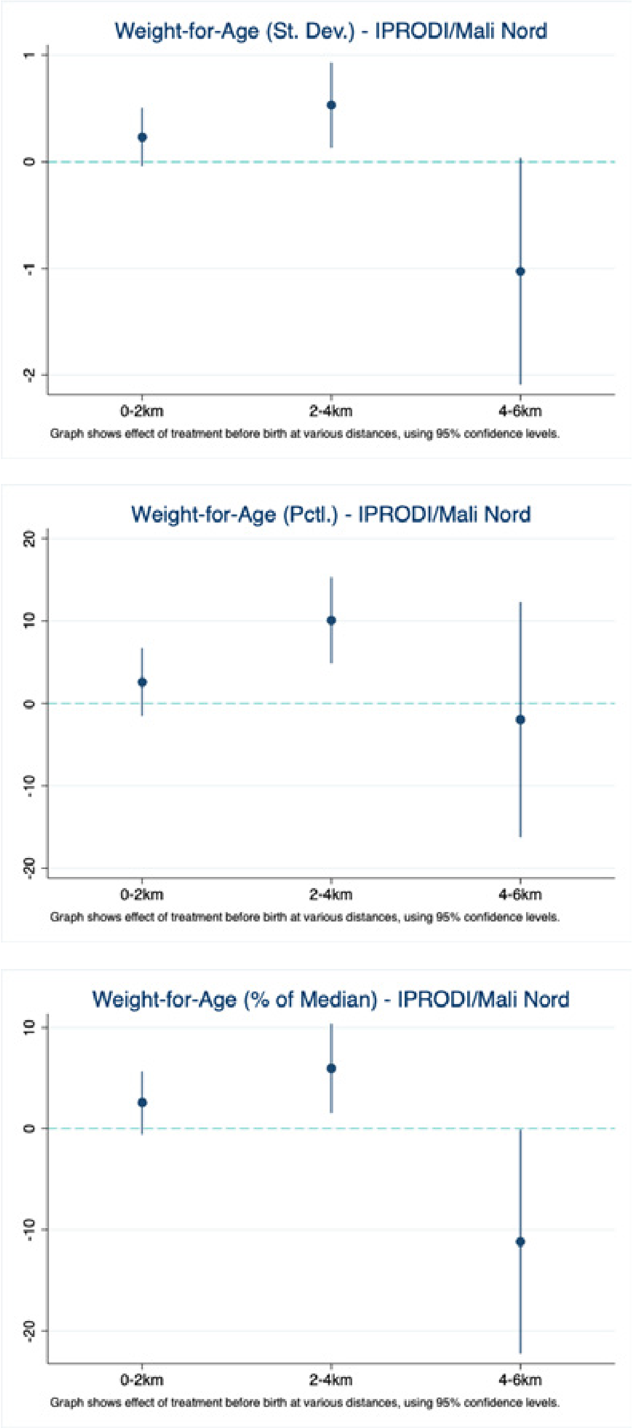
Table A2.10 Effect of treatment before birth on child wasting – IPRODI/Mali Nord

	(1)	(2)	(3)
	Weight-for-Age (Percentile)	**Weight-for-Age (Std. Dev.)**	**Weight-for-Age (% of Median)**
Treated Before Birth (0-2km)	2.581	0.230*	2.560
	(2.020)	(0.133)	(1.521)
Treated Before Birth (2-4km)	10.08***	0.531**	5.969**
	(2.541)	(0.195)	(2.138)
Treated Before Birth (4-6km)	-2.003	-1.028*	-11.20**
	(6.908)	(0.515)	(5.362)
Observations	1,603	1,603	1,603
R-squared	0.092	0.111	0.085
Region FEs	Y	Y	Y
Cohort FEs	Y	Y	Y

Source: authors' own table

*Note: Weight-for-age is a measure of wasting relative to other children of the same age. Weight-for-age is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.6 Effect of irrigation before birth on child wasting



Source: DEval's own figure

Note: This figure shows the estimated treatment effect on child wasting (weight-for-age) at different distance bands from the project location. Treatment is considered nearby project completion prior to birth. Weight-for-age is measured as standard deviations from the reference median in the upper graph, as percentile in in the middle graph, and as percentage of reference median in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.10.

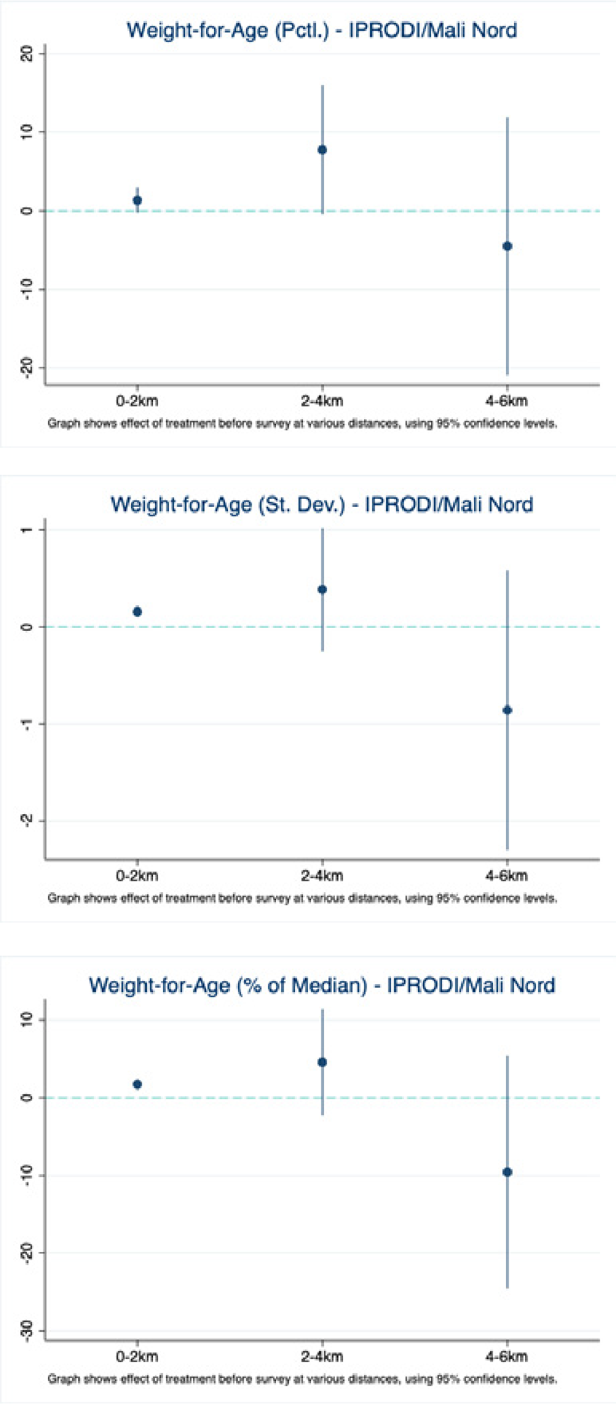
Table A2.11 Effect of irrigation before survey on child wasting in IPRODI/Mali Nord

	(1)	**(2)**	**(3)**
	Weight-for-Age (Percentile)	**Weight-for-Age (Std. Dev.)**	**Weight-for-Age (% of Median)**
Treated Before Survey (0-2km)	1.370*	0.155***	1.724***
	(0.575)	(0.0200)	(0.255)
Treated Before Survey (2-4km)	7.794*	0.383	4.562
	(2.966)	(0.228)	(2.472)
Treated Before Survey (4-6km)	-4.501	-0.859	-9.574
	(5.912)	(0.519)	(5.399)
Observations	1,603	1,603	1,603
R-squared	0.007	0.021	0.020
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Weight-for-age is a measure of wasting relative to other children of the same age. Weight-for-age is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.7 Effect of irrigation before survey on child wasting



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child wasting (weight-for-age) at different distance bands from the project location. Treatment is considered nearby project completion prior to the survey. Weight-for-age is measured as percentile in the upper graph, as standard deviations from the reference median in the middle graph and as percent of the reference median in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.11.

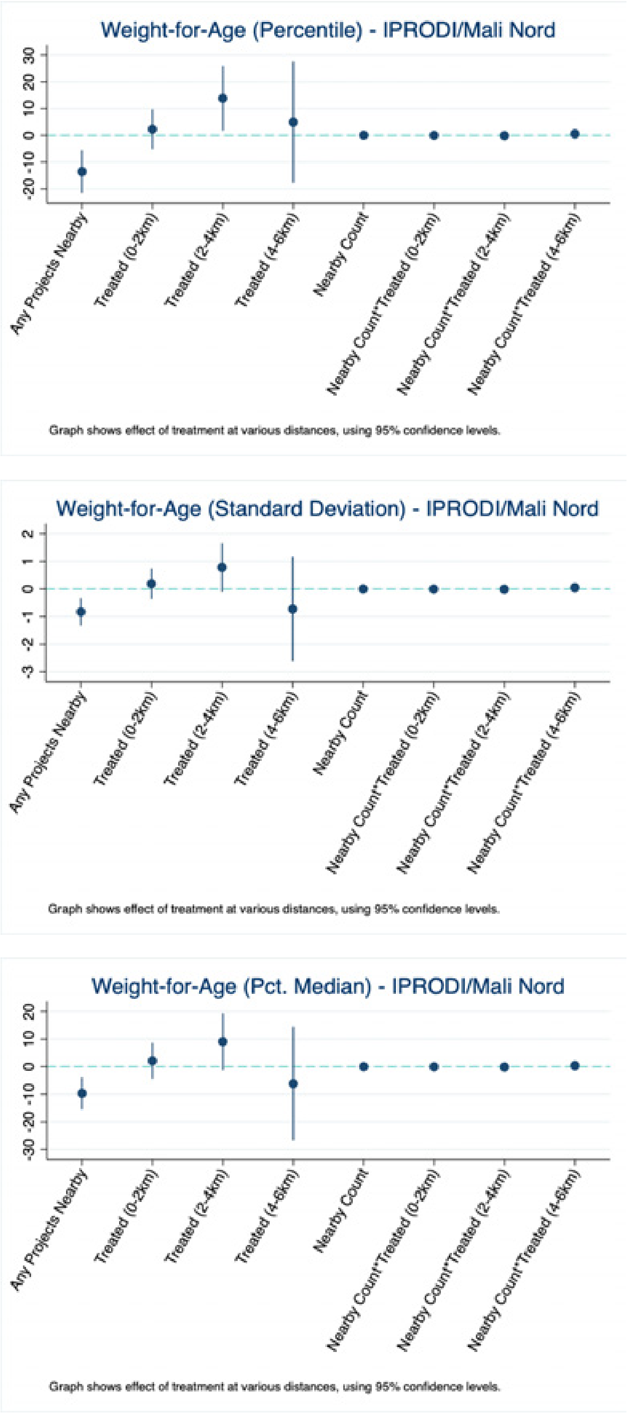
Table A2.12 Effect of treatment before birth on child wasting with nearby project controls

	(1)	(2)	(3)
	Weight-for-Age (Percentile)	**Weight-for-Age (St. Dev.)**	**Weight-for-Age (% of Median)**
Nearby Any	-13.59***	-0.830***	-9.673***
	(3.814)	(0.233)	(2.759)
Nearby Count	0.0351	0.00313	0.0274
	(0.0623)	(0.00471)	(0.0555)
Max Nearby Count	3.09e-05	0.000108	0.00440
	(0.0305)	(0.00193)	(0.0234)
Treated Before Birth (0-2km)	2.301	0.191	2.124
	(3.588)	(0.269)	(3.143)
Treated Before Birth (2-4km)	13.86**	0.784*	9.088*
	(5.819)	(0.424)	(4.952)
Treated Before Birth (4-6km)	4.951	-0.724	-6.157
	(10.77)	(0.899)	(9.755)
Nearby Count*Treated Before Birth (0-2km)	-0.0129	-0.00101	-0.00818
	(0.0419)	(0.00374)	(0.0431)
Nearby Count*Treated Before Birth (2-4km)	-0.128	-0.00835	-0.103
	(0.125)	(0.0103)	(0.123)
Nearby Count*Treated Before Birth (4-6km)	0.554	0.0519	0.382
	(0.881)	(0.0747)	(0.813)
Observations	1,321	1,321	1,321
R-squared	0.118	0.141	0.113
Region FEs	Y	Y	Y
Cohort FEs	Y	Y	Y

Source: authors' own table

*Note: Weight-for-age is measured as percentiles in column 1, as standard deviations from the reference median in column 2, and as percent of the reference median in column 3. Nearby Any is a binary variable indicating whether there are any project sites that have been completed within 20 km, excluding the nearest. Nearby Count is a count of projects within 20 km that have been completed, excluding the nearest. Max Nearby Count is the number of projects within 20 km that have been completed by 2020. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.8 Effect of treatment before birth on child wasting with nearby project controls



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child wasting (weight-for-age) at different distance bands from the project location. It also shows the moderating effect of the number of other treated areas nearby on this treatment effect. Treatment is considered nearby project completion prior to birth. Weight-for-age is measured as percentiles in the upper graph, as standard deviations from the reference median in the middle graph and as percent of the reference median in the lower graph. Each point represents the estimated treatment effect on the outcome; each line represents the confidence interval for each point estimate. The figure is based on Table A2.12.

Table A2.13 Effect of treatment before birth on child body mass – IPRODI/Mali Nord

	(1)	(2)	(3)
	Weight-for-Height (Percentile)	Weight-for-Height (Std. Dev.)	Weight-for-Height (% of Median)
Treated Before Birth (0-2km)	2.381	0.128	1.221
	(3.172)	(0.0912)	(0.914)
Treated Before Birth (2-4km)	6.513	0.272	3.425
	(4.605)	(0.271)	(2.398)
Treated Before Birth (4-6km)	2.263	-0.389	-2.844
	(12.99)	(0.895)	(8.462)
Observations	1,628	1,628	1,628
R-squared	0.052	0.057	0.053
Region FEs	Y	Y	Y
Cohort FEs	Y	Y	Y

Source: authors' own table

*Note: Weight-for-height is a measure of body mass relative to other children of the same age. Weight-for-height is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of the reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

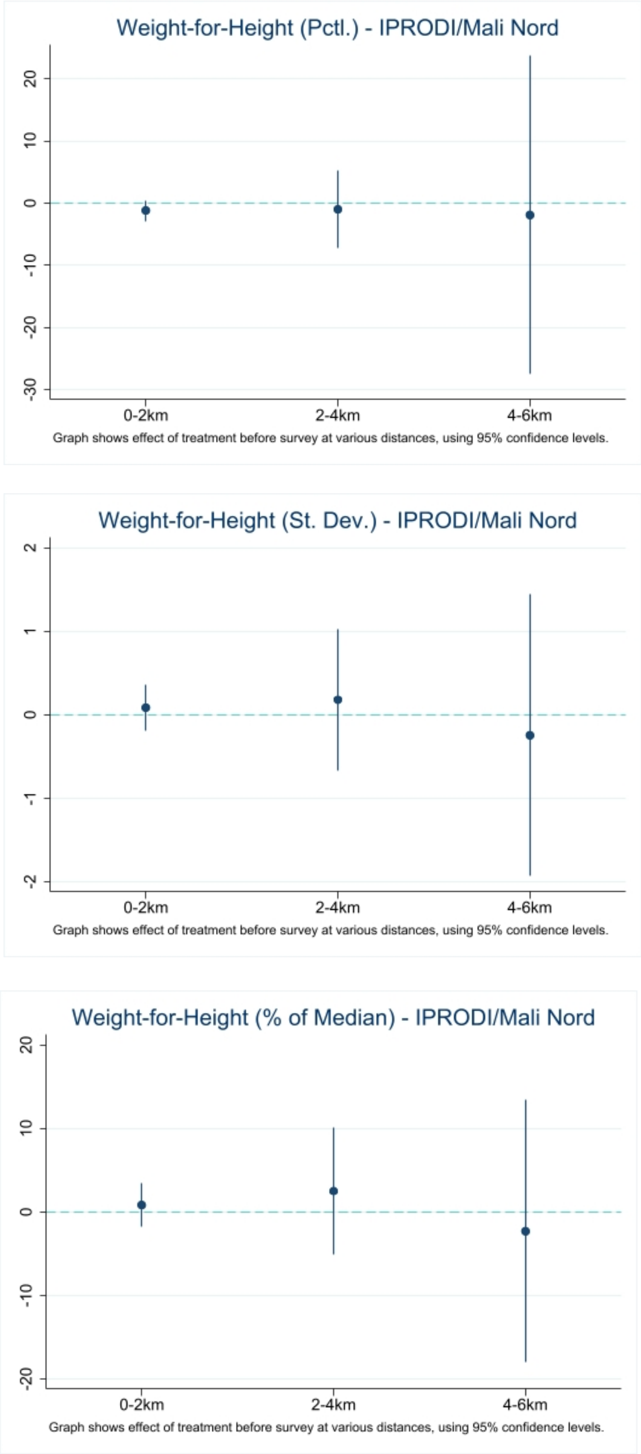
Table A2.14 Effect of treatment before survey on child body mass – IPRODI/Mali Nord

	(1)	(2)	(3)
	Weight-for-Height (Percentile)	**Weight-for-Height (Std. Dev.)**	**Weight-for-Height (% of Median)**
Treated Before Survey (0-2km)	1.228	0.0860	0.810
	(1.915)	(0.0998)	(0.941)
Treated Before Survey (2-4km)	4.543	0.179	2.509
	(5.336)	(0.307)	(2.740)
Treated Before Survey (4-6km)	0.929	-0.243	-2.283
	(9.592)	(0.608)	(5.661)
Observations	1,628	1,628	1,628
R-squared	0.014	0.020	0.021
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Weight-for-height is a measure of body mass relative to other children of the same age. Weight-for-height is measured as percentile in column 1, as standard deviations from the reference median in column 2, and as percentage of the reference median in column 3. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

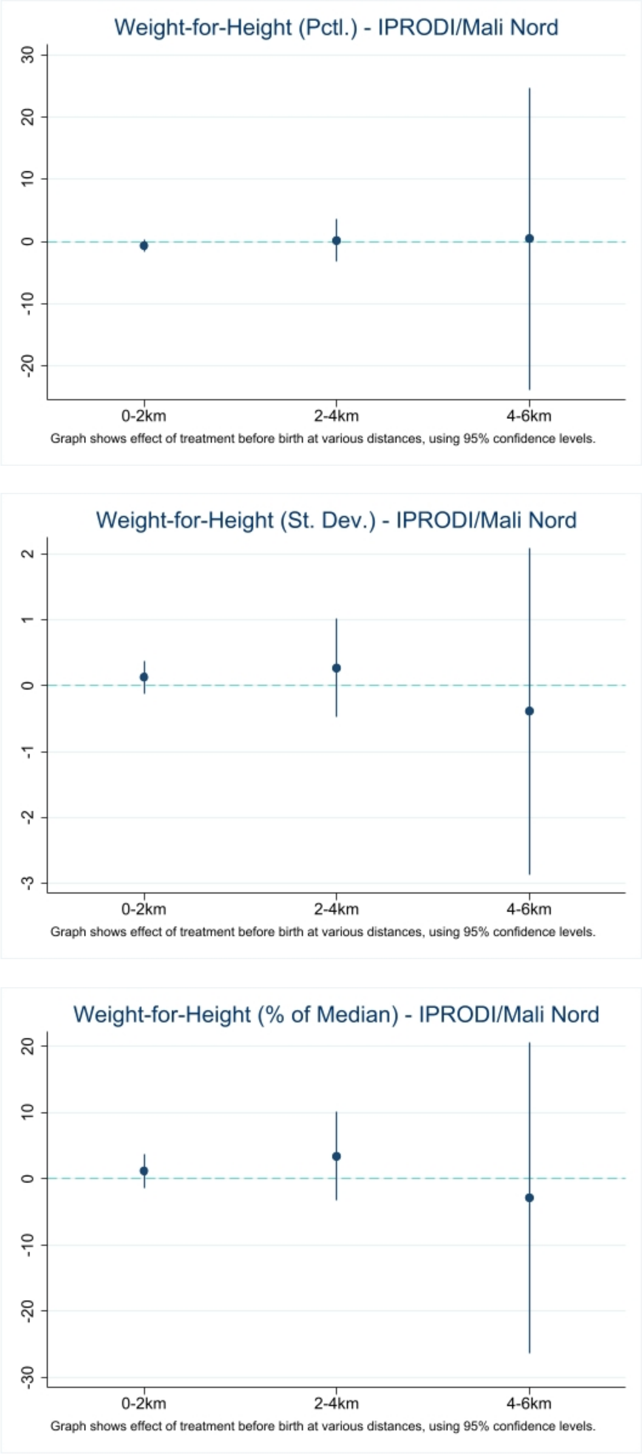
Figure A2.9 Effect of treatment before survey on child body mass



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child body mass (weight-for-height) at different distance bands from the project location. Weight-for-height is measured as percentiles in the upper graph, as standard deviations from the reference median in the middle graph and as percent of the reference median in the lower graph. Each point represents the mean difference in the outcome between the treatment and the control group; each line represents the confidence interval for each point estimate. The figure is based on Table A2.12.

Figure A2.10 Effect of treatment before birth on child body mass



Source: authors' own figure

Note: This figure shows the estimated treatment effect on child body mass (weight-for-height) at different distance bands from the project location. Weight-for-height is measured as percentiles in the upper graph, as standard deviations from the reference median in the middle graph and as percent of the reference median in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.13.

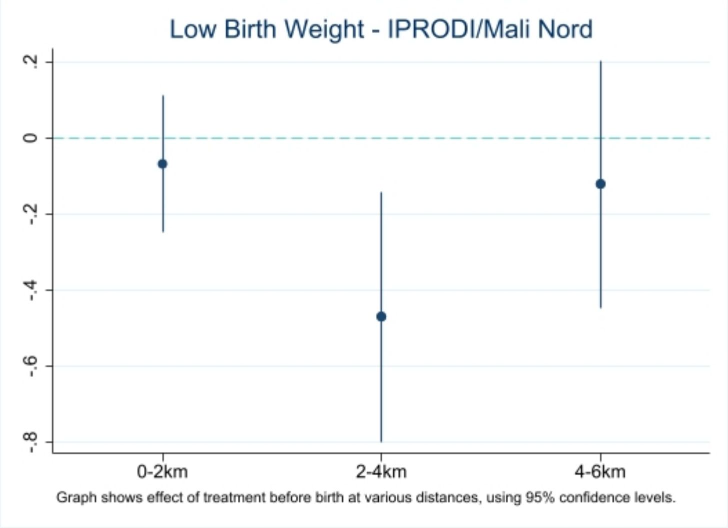
Table A2.15 Effect of treatment before birth on low birth weight - IPRODI/Mali Nord

	(1)
	Low Birth Weight
Treated Before Birth (0-2km)	-0.0679
	(0.0860)
Treated Before Birth (2-4km)	-0.470***
	(0.158)
Treated Before Birth (4-6km)	-0.121
	(0.157)
Observations	291
R-squared	0.120
Region FEs	Y
Cohort FEs	Y

Source: authors' own table

*Note: Low birth weight is a binary variable indicating whether a baby weighed less than 2.5 kg at birth. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.11 Effect of Treatment Before Birth on Low Birth Weight



Source: authors' own figure

Note: This figure shows the estimated treatment effect on low birth weight (<2.5 kg at birth) at different distance bands from the project location. Low birthweight is measured as a binary variable, with 1 indicating the child was born at a low birth weight, or a weight of less than 2.5kg. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.15.

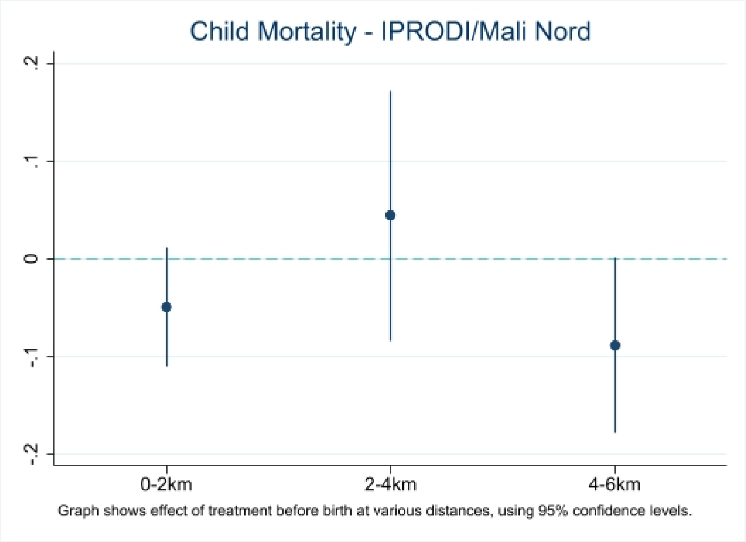
Table A2.16 Effect of treatment before age 5 on child mortality – IPRODI/Mali Nord

	(1)
	Child Mortality
Treated Before Age 5 (0-2km)	-0.0495
	(0.0304)
Treated Before Age 5 (2-4km)	0.0443
	(0.0638)
Treated Before Age 5 (4-6km)	-0.0888*
	(0.0448)
Observations	6,053
R-squared	0.041
Region FEs	Y
Cohort FEs	Y

Source: authors' own table

*Note: Child mortality is a binary variable indicating whether a child has died by age 5. Sample includes children within 6 km of a project site that are aged 5+ when surveyed. SEs clustered two-way by survey cluster and cohort. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.12 Effect of treatment before age 5 on child mortality



Source: authors' own figure

This figure shows the estimated treatment effect on child mortality (death before age 5) at different distance bands from the project location. Child mortality is measured as a binary variable indicating if a child died before reaching age 5. Each point represents the estimated treatment effect on the outcome; each line represents the confidence interval for each point estimate. The figure is based on Table A2.16.

Table A2.17 Effect of treatment before survey on child illness – IPRODI/Mali Nord

	(1)	**(2)**	**(3)**
	Anaemia	**Diarrhoea**	**Fever or Cough**
Treated Before Survey (0-2km)	0.0627	0.00103	0.0146
	(0.0468)	(0.00526)	(0.0642)
Treated Before Survey (2-4km)	0.00649	0.0368	0.0805**
	(0.491)	(0.0181)	(0.0274)
Treated Before Survey (4-6km)	0.165	0.0177	-0.159
	(0.215)	(0.0399)	(0.0944)
Observations	619	1,903	1,890
R-squared	0.044	0.058	0.128
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors’ own table

*Note: Anemia is a categorical variable with values 0-3, indicating whether a child has no, mild, moderate, or severe anemia as measured by a blood test. Diarrhea is a binary variable indicating whether a child had diarrhea in the past 2 weeks. Fever or cough is a binary variable indicating whether a child had either fever or cough in the past 2 weeks. Sample includes children within 6 km of a project site that are under 5 when surveyed. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

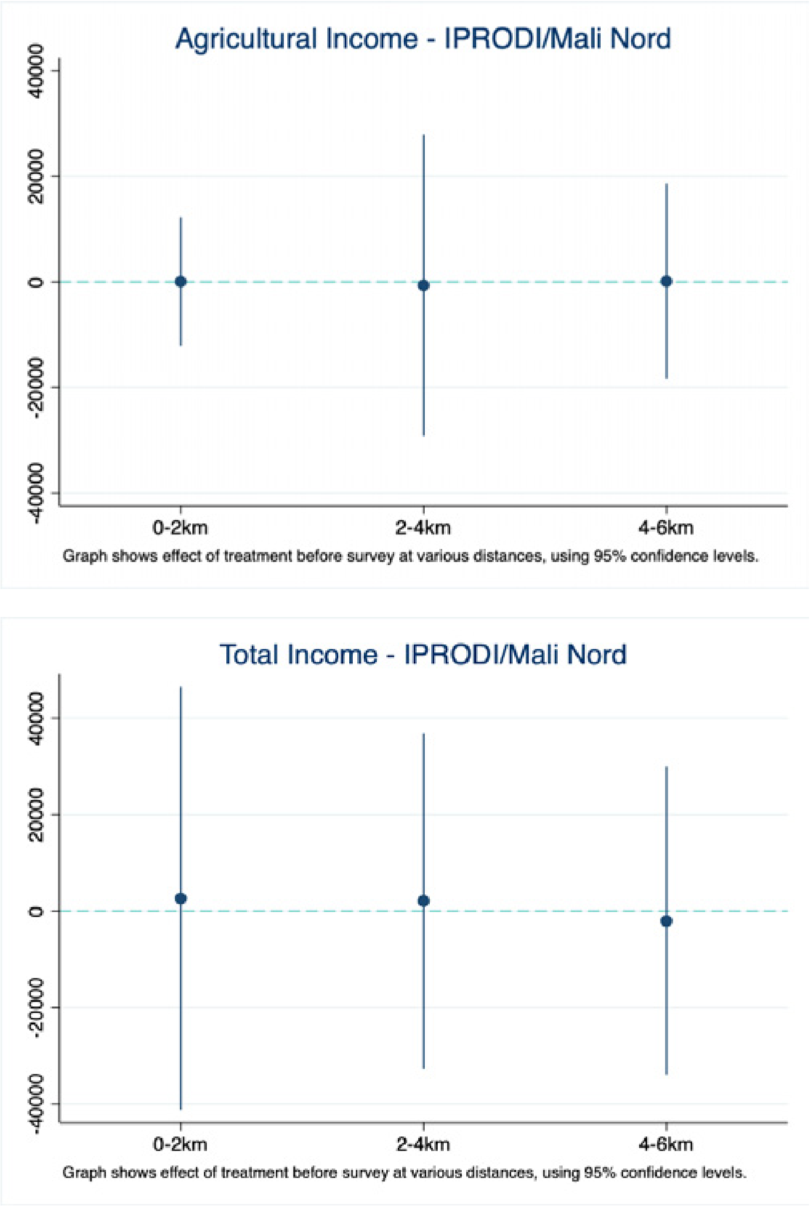
Table A2.18 Effect of treatment on agricultural and total household income – IPRODI/Mali Nord

	(1)	**(2)**
	Agricultural Income	**Total Income**
Treated Before Survey (0-2km)	76.05	2,609
	(191.6)	(3,447)
Treated Before Survey (2-4km)	-638.6	2,096
	(448.4)	(2,738)
Treated Before Survey (4-6km)	130.3	-2,051
	(290.3)	(2,508)
Observations	695	695
R-squared	0.223	0.036
Cercle FEs	Y	Y
Wave FEs	Y	Y

Source: authors' own table

*Note: Agricultural income and total income are measures of annual household income in Franc CFA (FCFA). Agricultural income consists of total sales from dairy, meat, livestock, animal skins, fish, eggs, tree products and crop harvests. Total income consists of agricultural income plus government benefits and assistance, cash transfers and remittances, and non-agricultural sources of income such as job salaries. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.13 Effect of irrigation on agricultural and total household income



Source: authors’ own figure

This figure shows the estimated treatment effect on annual household income at different distance bands from the project location. The upper graph considers only agricultural income as the outcome, and the lower graph considers all income. Each point represents estimated treatment effects on the outcome for each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.18.

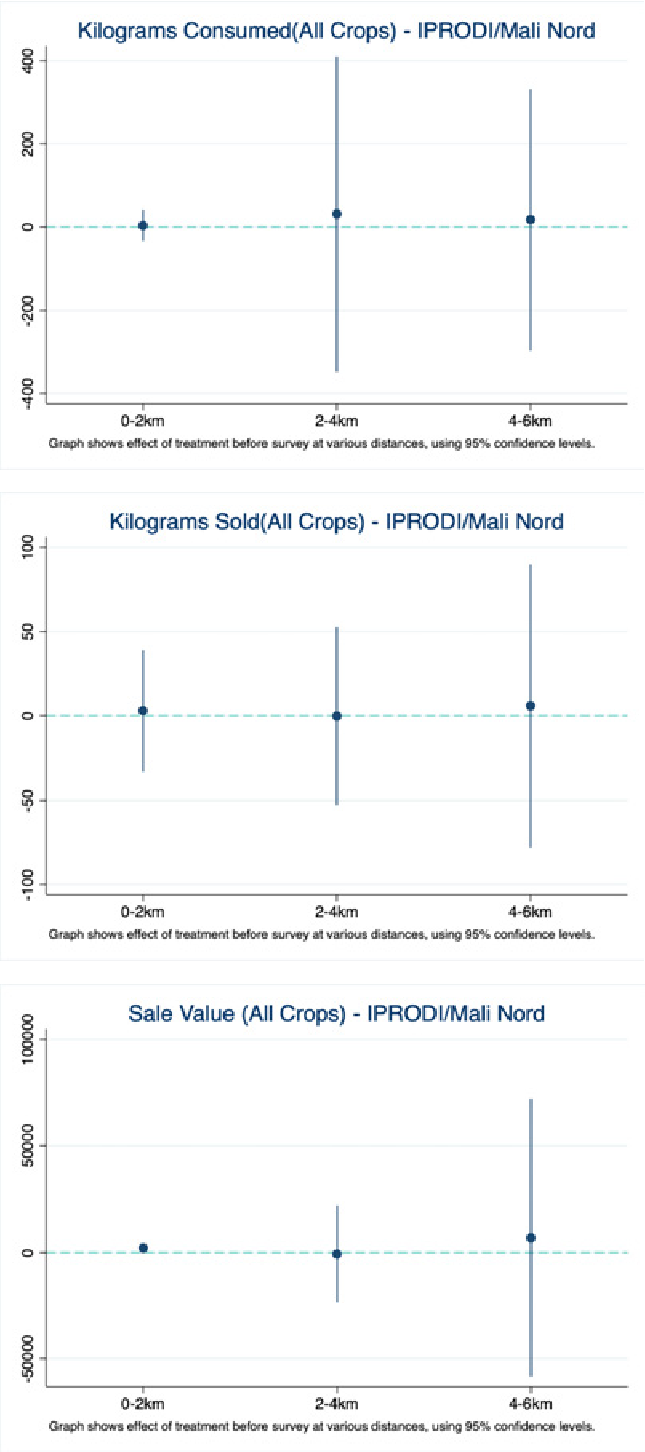
Table A2.19 Effect of irrigation on crop sale value, kilograms of crops sold and consumed – IPRODI/Mali Nord

	(1)	(2)	(3)
	Crop Sale Value	**Kilograms Sold**	**Kilograms Consumed**
Treated Before Survey (0-2km)	2,103**	2.947	3.194
	(117.5)	(2.827)	(2.953)
Treated Before Survey (2-4km)	-783.3	-0.183	31.18
	(1,778)	(4.146)	(29.86)
Treated Before Survey (4-6km)	6,843	5.880	17.36
	(5,134)	(6.617)	(24.79)
Observations	592	592	592
R-squared	0.039	0.051	0.185
Wave FEs	Y	Y	Y
Cercle FEs	Y	Y	Y

Source: authors' own table

*Note: Crop sale value is a measure in FCFA of household income from the annual harvest. Kilograms sold and consumed are measures of the same yearly harvest at the household level. Crops consist of market garden products such as vegetables and herbs, as well as the main staples such as millet, sorghum, rice, corn, and peanuts. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.14 Effect of irrigation on volume and value of harvest



Source: authors' own figure

This figure shows the estimated treatment effect on yearly harvest of all crops at different distance bands from the project location. Kilograms consumed of harvest is shown in the upper graph; kilograms sold of harvest is shown in the middle graph; and sale value of harvest is shown in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.19 (from top to bottom respectively column 3, 2 and 1).

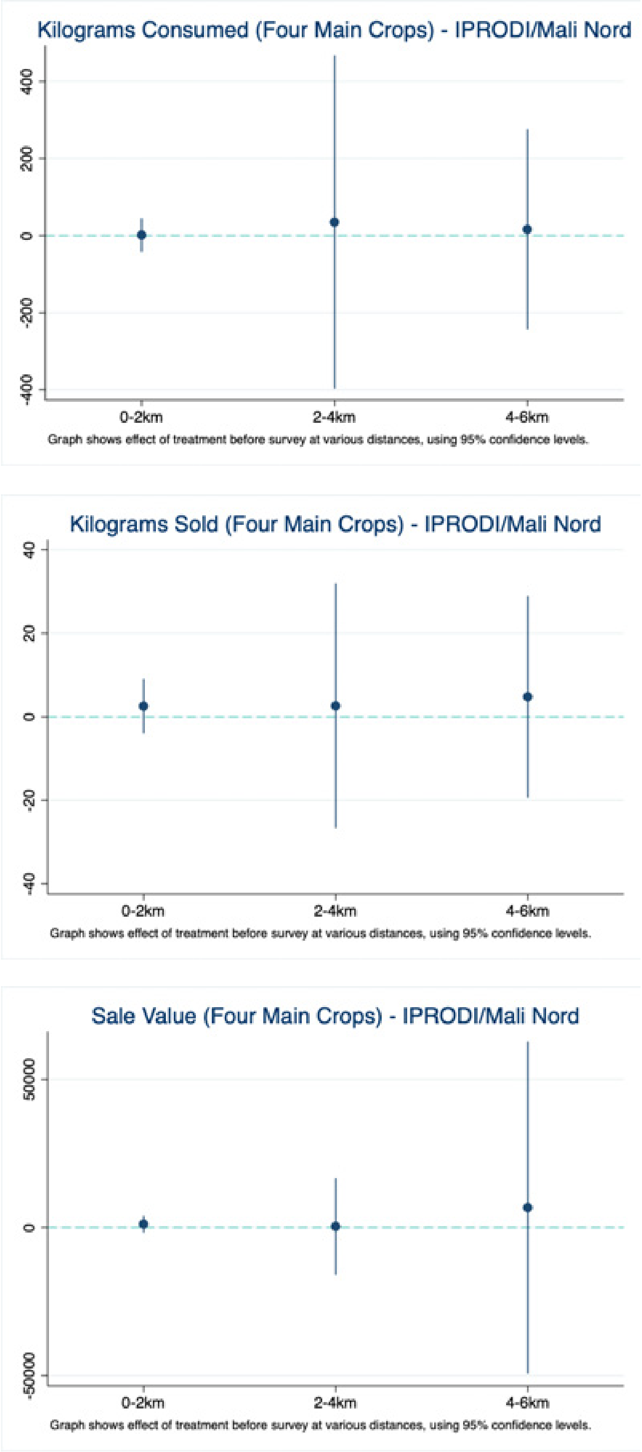
Table A2.20 Effect of irrigation on production and consumption of millet, sorghum, rice, and corn – IPRODI/Mali Nord

	(1)	(2)	(3)
	Crop Sale Value	Kilograms Sold	Kilograms Consumed
Treated Before Survey (0-2km)	1,126	2.551	1.534
	(225.7)	(0.512)	(3.442)
Treated Before Survey (2-4km)	356.2	2.631	35.02
	(1,285)	(2.306)	(34.02)
Treated Before Survey (4-6km)	6,708	4.791	16.29
	(4,413)	(1.902)	(20.41)
Observations	592	592	592
R-squared	0.047	0.054	0.189
Wave FEs	Y	Y	Y
Cercle FEs	Y	Y	Y

Source: authors' own table

*Note: Crop sale value is a measure in FCFA of household income from the annual harvest. Kilograms sold and kilograms consumed are measures of the same yearly harvest at the household level. Crops consist of millet, sorghum, rice and corn. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.15 Effect of irrigation on harvest of millet, sorghum, rice, and corn



Source: authors' own figure

This figure shows the estimated treatment effect on the yearly harvest from the four staple foods of millet, sorghum, rice, and corn at different distance bands from the project location. Kilograms consumed of harvest is shown in the upper graph; kilograms sold of harvest is shown in the middle graph; and sale value of harvest is shown in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.20 (from top to bottom respectively column 1, 2 and 3).

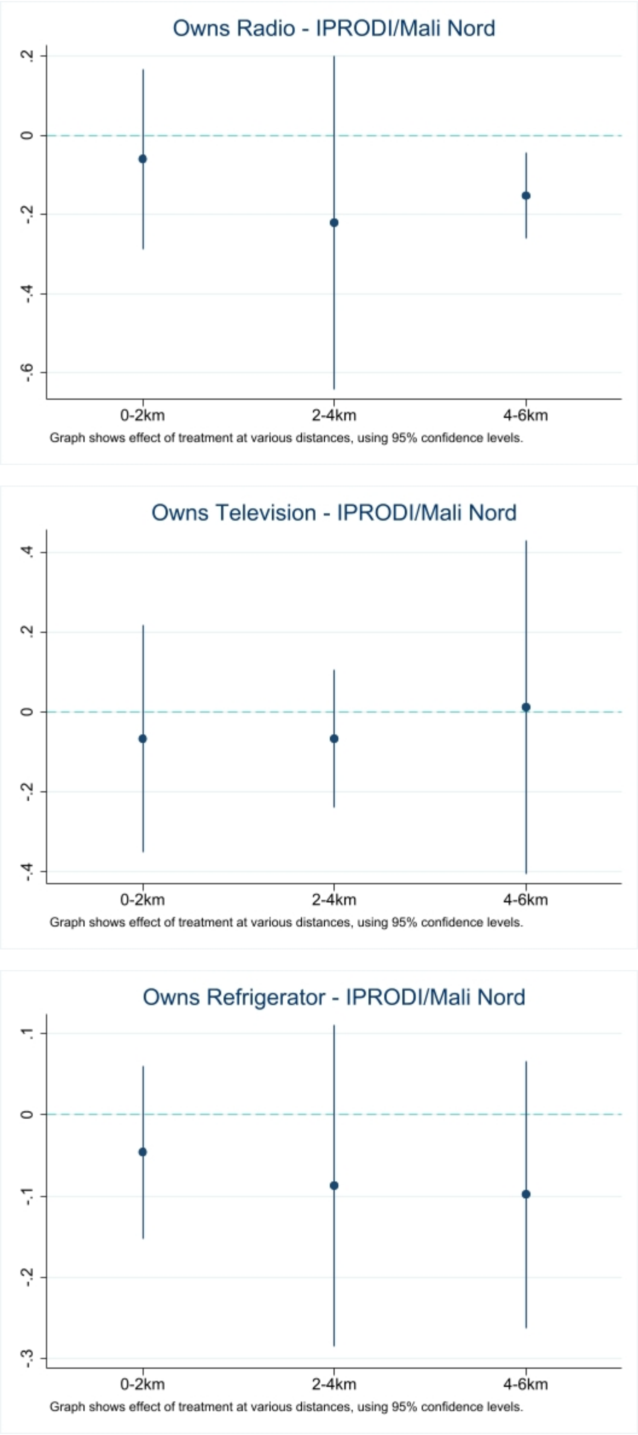
Table A2.21 Effect of irrigation on household assets – IPRODI/Mali Nord

	(1)	(2)	(3)
	Owns Radio	**Owns Television**	**Owns Refrigerator**
Treated Before Survey (0-2km)	-0.0597	-0.0671	-0.0461
	(0.0820)	(0.102)	(0.0383)
Treated Before Survey (2-4km)	-0.220	-0.0670	-0.0870
	(0.152)	(0.0619)	(0.0713)
Treated Before Survey (4-6km)	-0.152**	0.0123	-0.0980
	(0.0396)	(0.150)	(0.0593)
Observations	2,286	2,286	2,284
R-squared	0.047	0.101	0.097
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Outcome variables are binary variables indicating whether a household owns a good. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.16 Effect of irrigation on household assets



Source: authors' own figure.

This figure shows the estimated treatment effect on ownership of different goods at different distance bands from the project location. Ownership of a radio is shown in the upper graph; ownership of a television is shown in the middle graph; and ownership of a refrigerator is shown in the lower graph. Each point represents the mean difference in the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate.

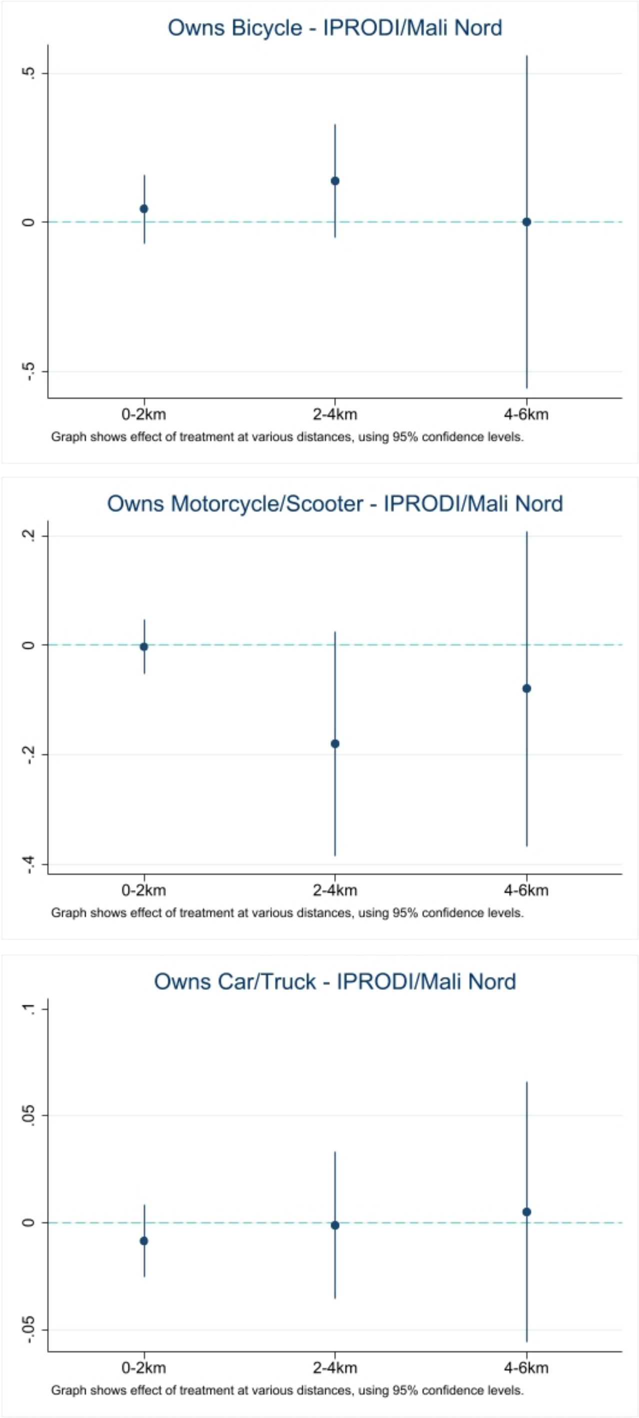
Table A2.22 Effect of irrigation on household transportation assets in IPRODI/Mali Nord

	(1)	(2)	(3)
	Owns Bicycle	Owns Motorcycle/Scooter	Owns Car/Truck
Treated Before Survey (0-2km)	0.0455	-0.00235	-0.00860
	(0.0416)	(0.0180)	(0.00615)
Treated Before Survey (2-4km)	0.140	-0.179*	-0.00131
	(0.0684)	(0.0737)	(0.0124)
Treated Before Survey (4-6km)	0.00232	-0.0789	0.00498
	(0.202)	(0.104)	(0.0219)
Observations	2,287	2,289	2,288
R-squared	0.102	0.055	0.011
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Outcome variables are binary variables indicating whether a household owns a good. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01*

Figure A2.17 Effect of irrigation on household transportation assets



Source: authors' own figure

This figure shows the estimated treatment effect on ownership of transportation assets at different distance bands from the project location. Ownership of a bicycle is shown in the upper graph; ownership of a motorcycle or scooter is shown in the middle graph; ownership of a car or truck is shown in the lower graph. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.22 (from top to bottom respectively column 1, 2 and 3).

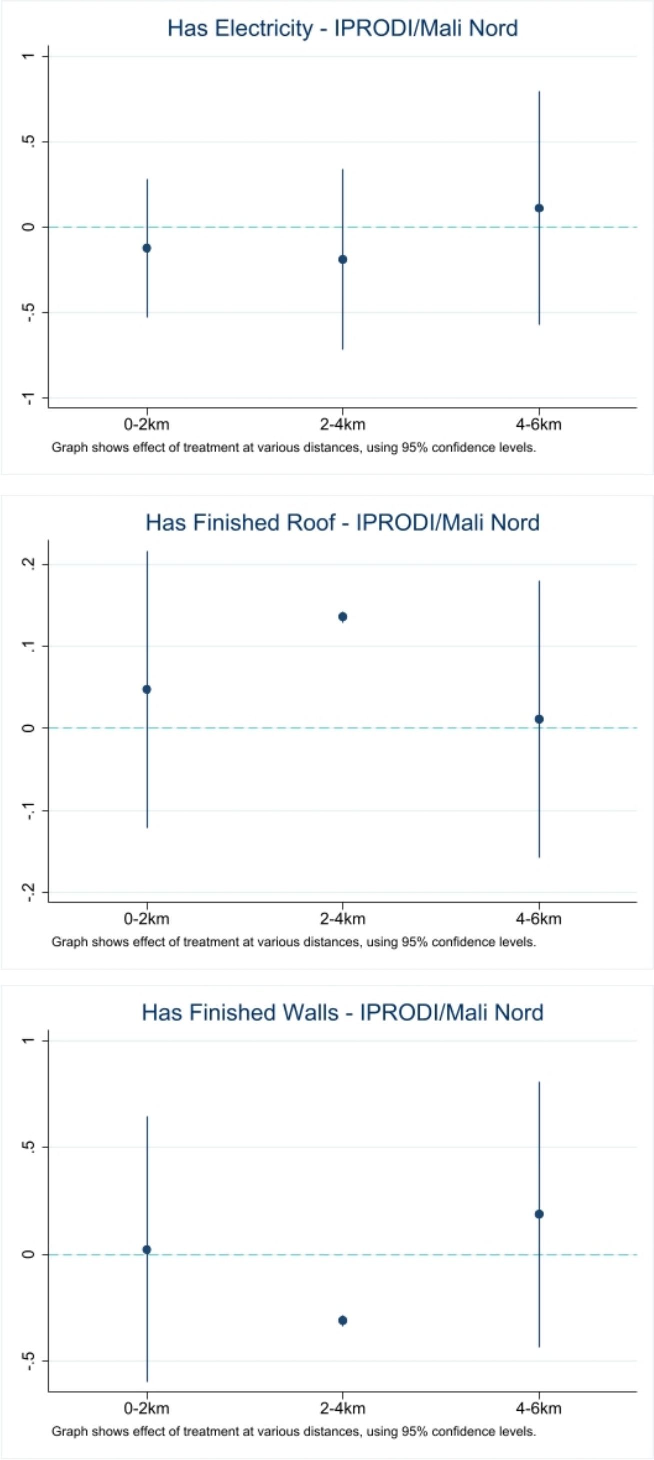
Table A2.23 Effect of irrigation on household dwelling quality in IPRODI/Mali Nord

	(1) Has Electricity	(2) Has Finished Roof	(3) Has Finished Walls
Treated Before Survey (0-2km)	-0.122	0.0477	0.0227
	(0.146)	(0.0133)	(0.0488)
Treated Before Survey (2-4km)	-0.190	0.136***	-0.310***
	(0.190)	(0.000532)	(0.00195)
Treated Before Survey (4-6km)	0.111	0.0113	0.187
	(0.247)	(0.0133)	(0.0488)
Observations	2,280	624	622
R-squared	0.155	0.133	0.072
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Outcome variables are binary variables indicating whether a household's residence has a quality. Sample includes households within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01*

Figure A2.18 Effect of irrigation on household dwelling quality



Source: authors' own figure

This figure shows the estimated treatment effect on household's dwelling quality at different distance bands from the project location. The upper graph shows the effect on electricity; the middle graph shows the effect on finished roofs; and the lower graph shows the effect on finished walls. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.23 (from top to bottom respectively column 1, 2 and 3).

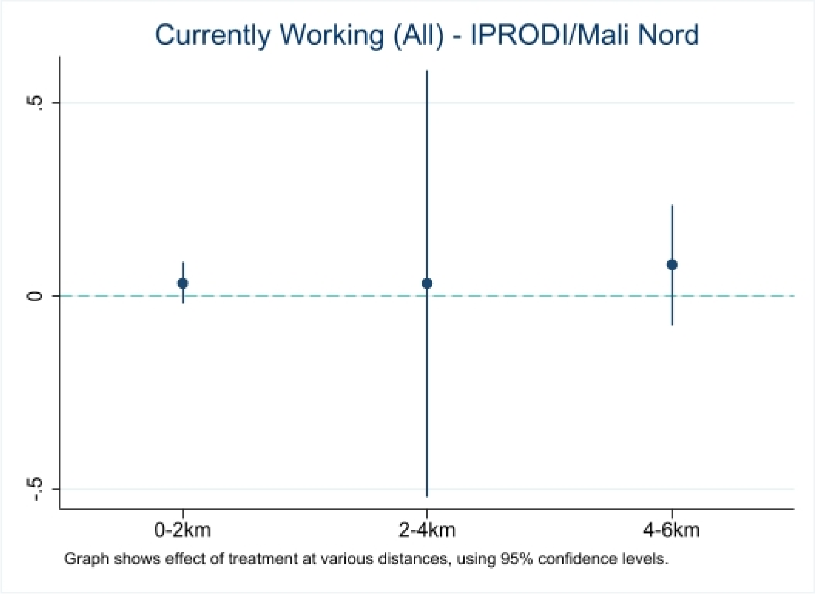
Table A2.24 Effect of irrigation on employment in IPRODI/Mali Nord

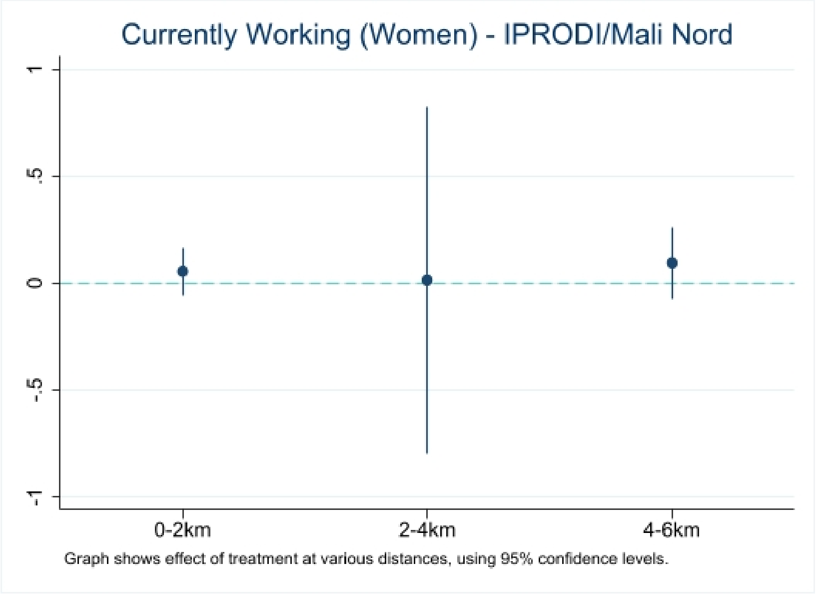
	(1)	**(2)**	**(3)**
	Currently working (All)	**Currently working (Men)**	**Currently working (Women)**
Treated Before Survey (0-2km)	0.0337	-0.0432	0.0539
	(0.0192)	(0.0606)	(0.0395)
Treated Before Survey (2-4km)	0.0334	0.146**	0.0146
	(0.200)	(0.0438)	(0.291)
Treated Before Survey (4-6km)	0.0825	-0.0860	0.0958
	(0.0564)	(0.0978)	(0.0601)
Observations	3,086	675	2,411
R-squared	0.040	0.133	0.077
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Currently working is a binary variable indicating whether respondents are currently working. Sample includes respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01*

Figure A2.19 Effect of irrigation on employment





Source: authors' own figure

This figure shows the estimated treatment effect on employment at different distance bands from the project location. The upper graph shows the effect on employment among all respondents; the lower graph shows the effect on employment among only female respondents. Employment is defined as currently working. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.24 (graph on top illustrates column 1 and graph below column 3).

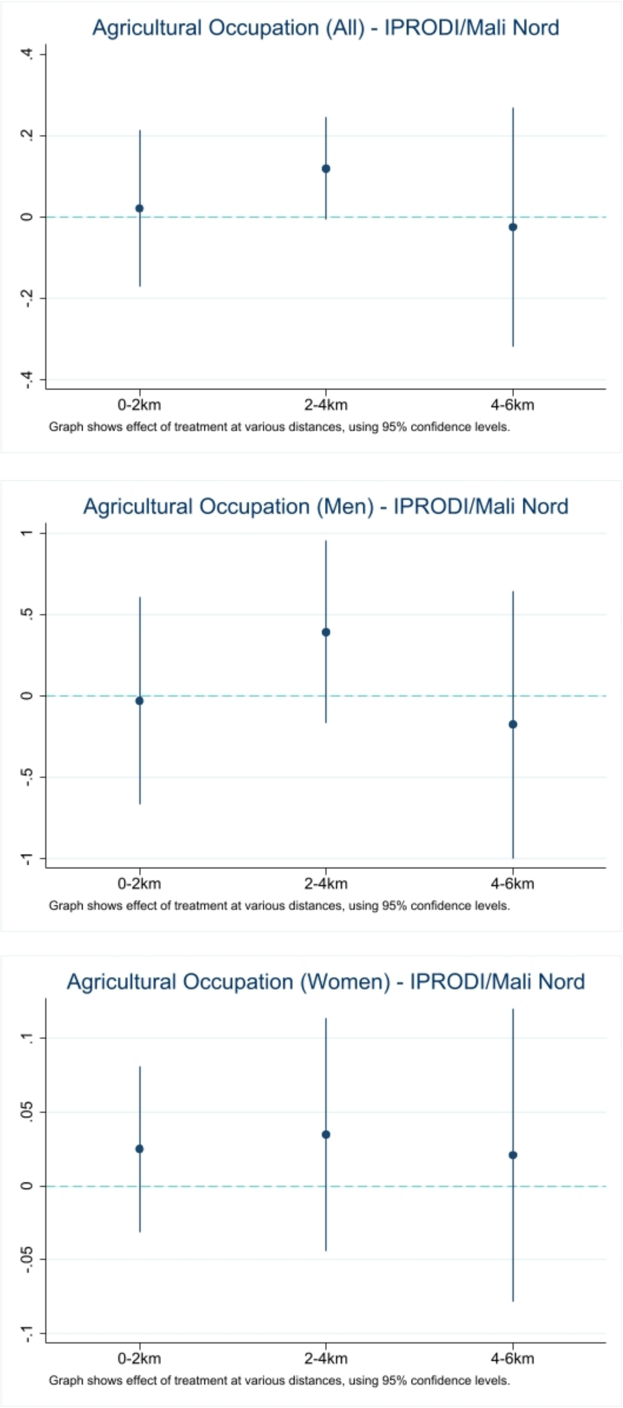
Table A2.25 Effect of irrigation on agricultural employment – IPRODI/Mali Nord

	(1)	(2)	(3)
	Agricultural occupation (All)	Agricultural occupation (Men)	Agricultural occupation (Women)
Treated Before Survey (0-2km)	0.0211	-0.0318	0.0249
	(0.0694)	(0.230)	(0.0203)
Treated Before Survey (2-4km)	0.119*	0.392	0.0348
	(0.0455)	(0.202)	(0.0284)
Treated Before Survey (4-6km)	-0.0249	-0.176	0.0208
	(0.106)	(0.296)	(0.0358)
Observations	3,061	668	2,393
R-squared	0.017	0.039	0.036
Region FEs	Y	Y	Y
Wave FEs	Y	Y	Y

Source: authors' own table

*Note: Agricultural occupation is a binary variable that is 1 if respondents have an agricultural occupation and 0 if they have a non-agricultural occupation or are not working. Sample includes respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.20 Effect of irrigation on agricultural employment



Source: authors' own figure

This figure shows in the estimated treatment effect on employment in agriculture at different distance bands from the project location. The upper graph shows the effect on agricultural occupation among all respondents; the middle graph shows the effect on agricultural occupation among only male respondents; and the lower graph shows the effect on agricultural occupation among only female respondents. Agricultural occupation is defined as reporting having an agricultural occupation. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.25 (from top to bottom respectively column 1, 2 and 3).

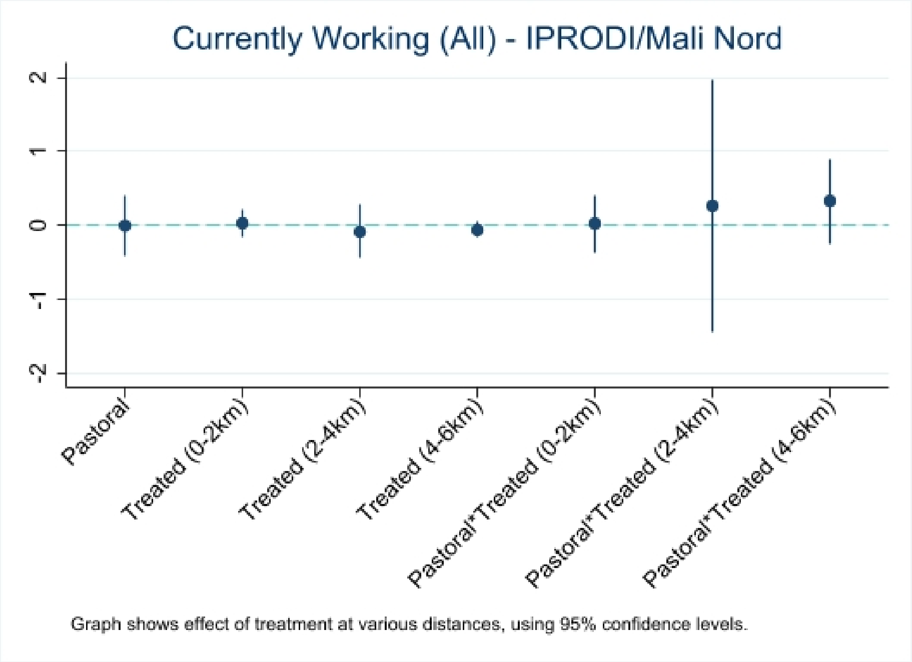
Table A2.26 Effect of irrigation on employment, with pastoral interaction – IPRODI/Mali Nord

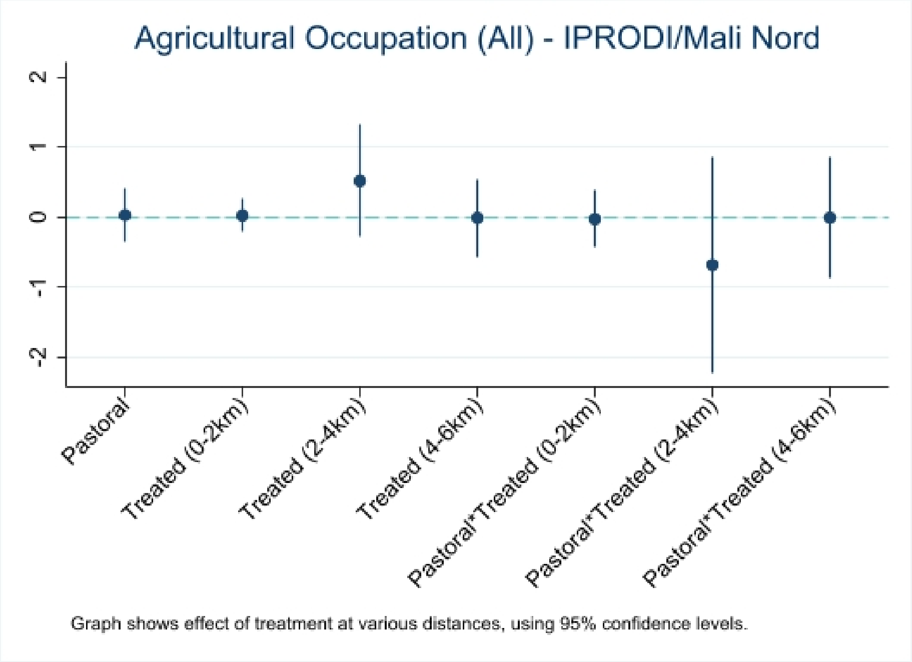
	(1)	(2)
	Currently working	**Agricultural occupation**
Pastoralism	-0.00544	0.0325
	(0.151)	(0.139)
Treated Before Survey (0-2km)	0.0307	0.0257
	(0.0691)	(0.0870)
Treated Before Survey (2-4km)	-0.0859	0.523
	(0.130)	(0.290)
Treated Before Survey (4-6km)	-0.0586	0.0198
	(0.0393)	(0.218)
Pastoralism*Treated Before Survey (0-2km)	0.0209	-0.0291
	(0.139)	(0.146)
Pastoralism*Treated Before Survey (2-4km)	0.266	-0.694
	(0.614)	(0.552)
Pastoralism*Treated Before Survey (4-6km)	0.327	-0.122
	(0.205)	(0.381)
Observations	2,805	2,815
R-squared	0.032	0.017
Region FEs	Y	Y
Wave FEs	Y	Y

Source: authors' own table

*Note: Currently working is a binary variable indicating whether respondents are currently working. Agricultural occupation is a binary variable that is 1 if respondents have an agricultural occupation and 0 if they have a non-agricultural occupation or are not working. Pastoralism is a continuous variable based on the ancestral pastoral characteristics of respondents' ethnic groups. Sample includes respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01*

Figure A2.21 Effect of irrigation on employment, with pastoral interaction





Source: authors' own figure

This figure shows in the estimated treatment effect on employment and employment in agriculture at different distance bands from the project location. It also shows the moderating effect of ancestral pastoral characteristics of the respondents' ethnic groups on the treatment effect. The upper graph shows employment, which is defined as currently working. The lower graph shows agricultural employment, which is defined as reporting an agricultural occupation. Each point represents the estimated treatment effect on the outcome at each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.26 (graph on top illustrates column 1 and graph below column 2).

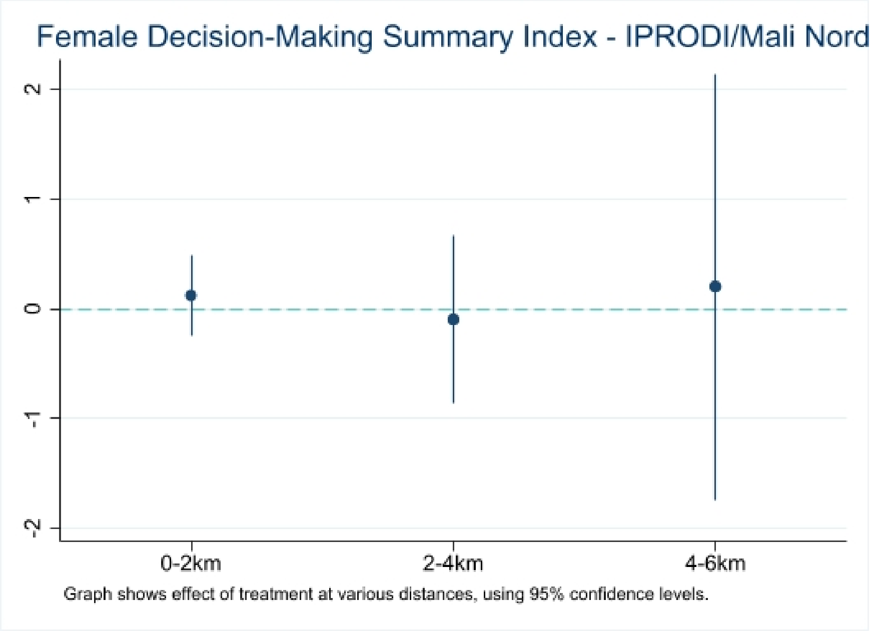
Table A2.27 Effect of irrigation on women's self-reported decision-making power in IPRODI/Mali Nord

	(1)	(2)	(3)	(4)	(5)
	Female Decision-Making Summary Index	**Woman Decider in Spending Own Income**	**Woman Decider in Own Healthcare**	**Woman Decider in Large HH Purchases**	**Woman Decider in Family Visits**
Treated Before Survey (0-2km)	0.120	-0.0364	0.0610*	-0.0126	0.0751
	(0.113)	(0.0224)	(0.0232)	(0.0342)	(0.0538)
Treated Before Survey (2-4km)	-0.0997	0.0825*	-0.122**	-0.0172	-0.00594
	(0.241)	(0.0344)	(0.0360)	(0.0309)	(0.135)
Treated Before Survey (4-6km)	0.200	-0.191	0.0963	-0.101**	0.104
	(0.609)	(0.0983)	(0.125)	(0.0227)	(0.331)
Observations	2,121	1,070	2,116	1,972	2,116
R-squared	0.030	0.046	0.012	0.004	0.060
Region FEs	Y	Y	Y	Y	Y
Wave FEs	Y	Y	Y	Y	Y

Source: authors' own table

*Note: Woman Decider in Spending Own Income is an indicator variable that is 1 if the respondent reports she has decision-making power in how to spend her income and 0 otherwise. Woman Decider in Own Healthcare is an indicator variable that is 1 if the respondent reports she has decision-making power in her healthcare and 0 otherwise. Woman Decider in Large HH Purchases is an indicator variable that is 1 if the respondent reports she has decision-making power in large household purchases and 0 otherwise. Woman Decider in Family Visits is an indicator variable that is 1 if the respondent reports she has decision-making power in visiting family and 0 otherwise. Female Decision-Making Summary Index is a summary index of all these variables weighted based on variation in the control group. Sample includes female respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.22 Effect of irrigation on women's self-reported decision-making power



Source: authors' own figure

This figure shows estimated treatment effect on self-reported decision-making power among women at different distance bands from the project location. The outcome variable is a summary index of reports on decision-making power in a number of domains. Each point represents estimated treatment effects on the outcome in each distance band; each line represents the confidence interval for each point estimate. The figure is based on Table A2.27, column 1.

Table A2.28 Effect of irrigation on women's opinion of IPV – IPRODI/Mali Nord

	(1)	(2)	(3)	(4)	(5)	(6)
	IPV Opinion Summary Index	**Beating Justified if Woman Goes Out w/o Permission**	**Beating Justified if Woman Neglects Children**	**Beating Justified if Woman Argues with Partner**	**Beating Justified if Woman Refuses Sex**	**Beating Justified if Woman Burns Food**
Treated Before Survey (0-2km)	-0.0742	0.00958	-0.153**	-0.0343	0.0611	-0.0681**
	(0.109)	(0.0991)	(0.0310)	(0.0438)	(0.0878)	(0.0184)
Treated Before Survey (2-4km)	-0.235*	-0.138	-0.0914	-0.139	-0.0245	-0.0836**
	(0.0967)	(0.144)	(0.0700)	(0.0692)	(0.0305)	(0.0207)
Treated Before Survey (4-6km)	0.0709	0.0902	-0.0644	0.127***	0.0776	-0.0459
	(0.263)	(0.118)	(0.180)	(0.0151)	(0.109)	(0.0937)
Observations	2,208	2,184	2,179	2,184	2,148	2,194
R-squared	0.203	0.114	0.151	0.163	0.179	0.112
Region FEs	Y	Y	Y	Y	Y	Y
Wave FEs	Y	Y	Y	Y	Y	Y

Source: authors' own table

*Note: Beating Justified if Woman Goes Out w/o Permission is an indicator variable that is 1 if the respondent believes a man is justified in beating his partner if she goes out without his permission and 0 if the respondent believes it is not justified. Beating Justified if Woman Neglects Children is an indicator variable that is 1 if the respondent believes a man is justified in beating his partner if she neglects her children and 0 if the respondent believes it is not justified. Beating Justified if Woman Argues with Partner is an indicator variable that is 1 if the respondent believes a man is justified in beating his partner if she argues with him and 0 if the respondent believes it is not justified. Beating Justified if Woman Refuses Sex is an indicator variable that is 1 if the respondent believes a man is justified in beating his partner if she refuses sex with him and 0 if the respondent believes it is not justified. Beating Justified if Woman Burns Food is an indicator variable that is 1 if the respondent believes a man is justified in beating his partner if she burns food and 0 if the respondent believes it is not justified. IPV Opinion Summary Index is a summary index of all these opinions weighted based on variation in the control group. Sample includes female respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

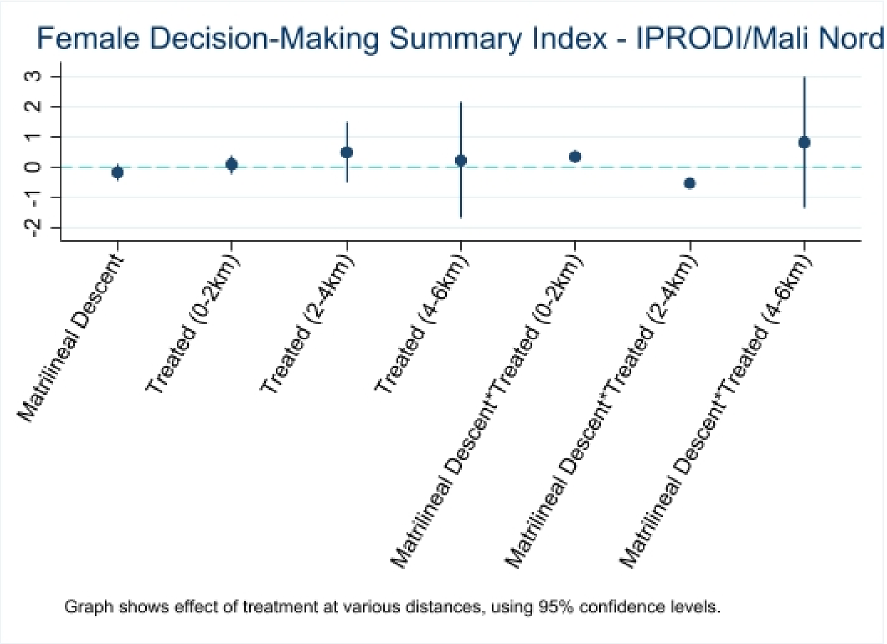
Table A2.29 Effect of irrigation on women's empowerment, with matrilineal descent interaction in IPRODI/Mali Nord

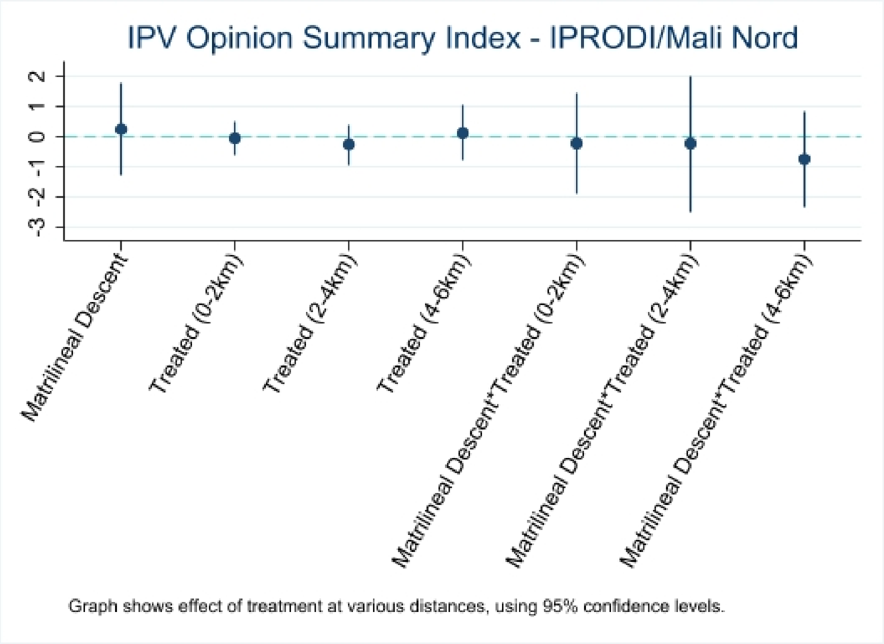
	(1)	(2)
	Female Decision-Making Summary Index	IPV Opinion Summary Index
Matrilineal Descent	-0.174	0.257
	(0.0894)	(0.477)
Treated Before Survey (0-2km)	0.0805	-0.0482
	(0.0986)	(0.175)
Treated Before Survey (2-4km)	0.487	-0.246
	(0.314)	(0.210)
Treated Before Survey (4-6km)	0.226	0.136
	(0.601)	(0.293)
Matrilineal Descent*Treated Before Survey (0-2km)	0.350**	-0.213
	(0.0532)	(0.526)
Matrilineal Descent*Treated Before Survey (2-4km)	-0.534***	-0.225
	(0.0223)	(0.709)
Matrilineal Descent*Treated Before Survey (4-6km)	0.806	-0.741
	(0.679)	(0.499)
Observations	1,931	2,016
R-squared	0.039	0.198
Region FEs	Y	Y
Wave FEs	Y	Y

Source: authors' own table

*Note: IPV Opinion Summary Index is a summary index of female respondents' opinions on IPV, weighted based on variation in the control group. Female Decision-Making Summary Index is a summary index of female respondents' self-reported decision-making power, weighted based on variation in the control group. Matrilineal descent is an indicator variable based on the ancestral matrilineal characteristics of respondents' ethnic groups. Sample includes female respondents within 6 km of a project site. SEs clustered two-way by survey cluster and wave. * p<0.1, ** p<0.05, *** p<0.01.*

Figure A2.23 Effect of irrigation on women's empowerment, with matrilineal descent interaction





Source: authors' own figure

This figure shows the estimated treatment effect on women's self-reported decision-making power (upper graph) and women's acceptance of violence against women (lower graph) at different distance bands from the project location. It also shows the moderating effect of ancestral matrilineal characteristics of respondents' ethnic groups on the treatment effects. Each point represents the estimated treatment effect on the outcome; each line represents the confidence interval for each point estimate. The figures are based on Table A2.29 (graph on top illustrates column 1 and graph below column 2).

Table A2.30 Effect of irrigation on yearly conflict events

	(1)	(2)	(3)
	Conflict	**Conflict**	**Conflict**
Treated (0-1km)	-0.132***	-0.106***	0.0999**
	(0.0418)	(0.0371)	(0.0407)
Treated (1-5km)	-0.0260**	-0.00985	0.0895**
	(0.0114)	(0.0233)	(0.0378)
Treated (5-10km)	0.105***	0.0880**	0.128**
	(0.0352)	(0.0404)	(0.0509)
Observations	59,400	11,250	43,200
R-squared	0.266	0.285	0.172
Cercle*Year FEs	Y	Y	Y
Project*Distance FEs	Y	Y	Y
Sample	IPRODI/Mali Nord Pump-based irrigation	IPRODI/Mali Nord Mares	Sikasso

Source: authors' own table

*Note: Conflict is a count variable of conflict events near project sites. SEs clustered two-way by project site and year. * p<0.1, ** p<0.05, *** p<0.01.*

Table A2.31 Effect of irrigation on yearly non-state conflict events

	(1)	(2)	(3)
	Conflict	**Conflict**	**Conflict**
Treated (0-1km)	-0.0946***	-0.0667***	0.0337
	(0.0292)	(0.0230)	(0.0520)
Treated (1-5km)	-0.0197**	-0.00407	0.0266
	(0.00810)	(0.0153)	(0.0469)
Treated (5-10km)	0.0797***	0.0630**	0.0481
	(0.0265)	(0.0266)	(0.0545)
Observations	59,400	11,250	43,200
R-squared	0.203	0.214	0.145
Cercle*Year FEs	Y	Y	Y
Project*Distance FEs	Y	Y	Y
Sample	IPRODI/Mali Nord Pump-based irrigation	IPRODI/Mali Nord Mares	Sikasso

Source: authors' own table

*Note: Conflict is a count variable of conflict events near project sites. Excludes conflicts with state actors. SEs clustered two-way by project site and year. * p<0.1, ** p<0.05, *** p<0.01.*