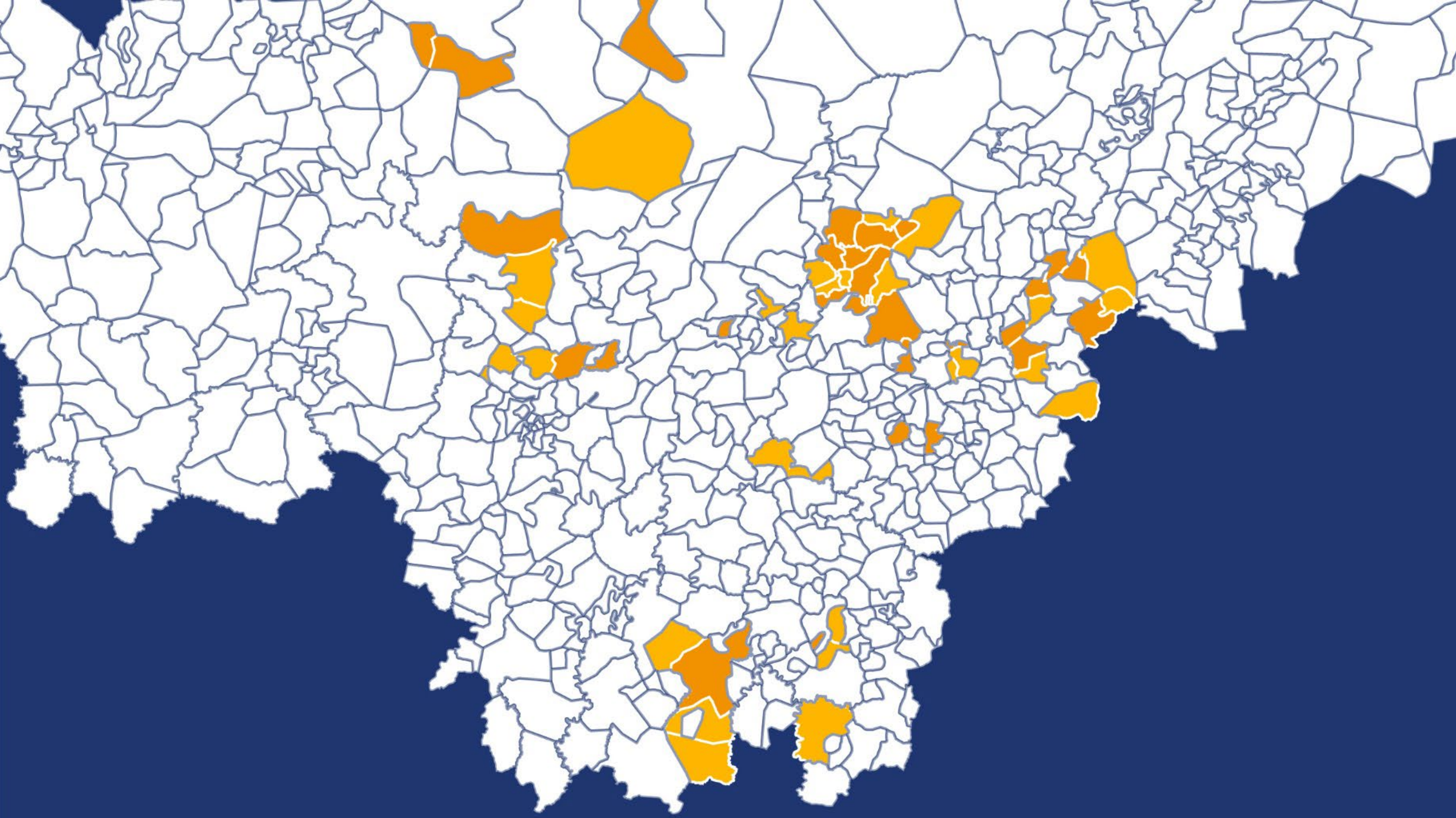

TECHNICAL REPORT

Using GIS as a potential methodology to assess the spillover (indirect) effects of IFAD's interventions

Authors

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IFAD
Investing in rural people

RESEARCH AND IMPACT

Authors

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Research and Impact – Technical Report

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Athur Mabiso is a senior technical specialist (economist) at the Research and Impact Division (RIA), IFAD. He works on impact assessments of IFAD-supported projects and conducts research on a variety of topics in development economics. Mabiso has extensive research experience in the areas of agricultural policy, rural investments, food security, health and nutrition. Prior to joining IFAD in 2018, Mabiso worked at the International Food Policy Research Institute, conducting research and engaging with policymakers and development partners in several developing countries in Africa and Asia. He holds a PhD in agricultural economics from Michigan State University, a master's in food and resource economics from the University of Florida and a bachelor's degree with honors in agriculture, from the University of Zimbabwe.

Eleonora Patacchini is the Stephen and Barbara Friedman Professor of International Political Economy at Cornell University. She specializes in applied economics and applied statistics. Her recent research focuses on the empirical analysis of behavioral models of strategic interactions for decision-making. She is the editor of the Journal of Economic Geography. Her work has been profiled in Bloomberg, PBS Newshour, The Independent, The Economist, and The New York Times, among others.

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Valerio Leone Sciabolazza is assistant professor at Sapienza University of Rome. Valerio is an applied economist who investigates how geography and social/economic linkages shape agents' decisions. Using a network perspective, he examines the structure of social and spatial relations, and assesses the impacts of these relations on economic outcomes. He conducts research in different lines of work, mainly political economy and development economics. He published on different topics including the spillover effects of conflicts on economic growth and migration behavior. He also worked as a consultant for several international agencies, such as IFAD, FAO, and the World Bank.

Background

During IFAD11 replenishment period (2019-2021), a total of 104 projects completed implementation across the world. Each IFAD-financed project consisted of various interventions designed to achieve IFAD's Strategic Goal and Objectives (SOs): i.e., economic mobility (goal), productive capacities (SO1), beneficial market access (SO2), resilience to climate change (SO3). The standard impact assessment approach followed by IFAD to determine the benefits produced by project interventions on the strategic goal and objectives has been to use ex post impact assessment data derived from Face-to-Face (F2F) interviews. These interviews are conducted with the beneficiary households (treatment group) as well as comparison households (control group). The interviews are conducted after the interventions have taken place (ex post), within a time window that differs from project to project, since each project's start (and completion) of implementation is different. The information collected from the household surveys for the impact assessments (IAs) is self-reported and based on the households' retrospective recollection.

In 2020, the standard approach of conducting F2F interviews for the IAs had to be halted as a consequence of the COVID-19 pandemic. As a result, IFAD explored alternative approaches to continuing its impact assessments. This report documents the extent to which GIS methods and secondary data can be used as a complementary set of tools to conduct the impact assessments of IFAD during the period when F2F interviews were not possible to implement.

Why use GIS methods?

The use of GIS is widespread in the economic and statistical analyses literature. GIS data are obtained from multiple open-source databases containing, for example, satellite data, remotely sensed data, digital terrain models, and it is often employed to map socio-economic data with a spatial component. They provide new data complementing official statistics when the latter are poorly measured or considered unreliable, and generate additional spatial inputs to statistical and econometric analyses.

GIS methods can be used to obtain socio-economic indicators, living standards measures, land resources and environmental data, and vegetation indexes, among others. As a result, GIS methods may be employed to estimate economic growth, the spread of economic activities, the quality of political institutions, the accessibility to (or remoteness of) specific areas, the geographical distribution of agricultural practices, the development of infrastructure networks, environmental policies, and conflicts.[1] Moreover, GIS has been also used to design credible counterfactual data to rigorously assess the impact of interventions.[2]

Finally, GIS methods represent a valuable complement to the information usually collected through ex-post F2F interviews. In fact, GIS methods can generate longitudinal or panel data (as well as time series data), which provide a reliable measure of the conditions of the treated areas before and after an intervention took place. On the contrary, when using ex post F2F interviews, a change in the condition of the beneficiaries of an intervention can only be assessed through the recall data collected, which can introduce sources of bias in the analyses.

The design of empirical analysis using GIS methods in relation to IFAD projects

A prerequisite for using GIS methods in household-level impact assessments is that one first of all needs geo-referenced data at the level of the household. This information is needed for both the beneficiary (treated) households and comparison (control) households. However, this information is only available for a small number of IFAD's projects and in some cases only for the beneficiary households. Moreover, one should dedicate a large effort to produce reliable measures at the household level for every outcome of interest for IFAD.

A solution to this problem is to change the unit of observation of the study, shifting from household to community-level analyses. The location of the communities where targeted households reside can be easily obtained from the M&E database of IFAD as well as from the impact assessments data (for those sampled for a baseline or mid-line household survey). These geolocation data can then be linked to various remote sensing databases enabling access to a variety of relevant variables that can be retrieved using satellite data. When the analysis is performed using aggregated information at the community-level, a number of proxies must thus be constructed to observe the outcome of an intervention. For instance, this can be done by registering improvements in the socio-economic conditions of targeted communities, such as changes in population travel time, improvements in observable infrastructure such as roads and buildings (settlements), growth of agricultural assets, and changes in land productivity, etc.

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[1] See Chen et al. (2013), Henderson et al. (2012), Hodler and Raschky (2014), Donaldson and Hornbeck (2016), Michalopoulos and Papayoannu (2016), Rogall (2021), and Yanagizawa-Drott (2014), among others.

[2] Relevant contributions in this strand of research are Banerjee et al. (2020), Dinkelman (2011), Duflo and Pande (2007), Faber (2014), Michaels (2008), Michalopoulos and Papayoannu (2013), Nunn (2008), and Qian (2008).

Application of GIS impact assessment to IFAD projects

In this report, we provide an example of how GIS methods can be applied to assess the impact of IFAD's intervention by using two case studies: Ethiopia and Mali. In both countries, IFAD implemented projects focused on improving rural households' access to a range of financial services, in order to improve their agricultural productivity and incomes.

Since interventions in these countries were conducted to improve the agricultural productivity and production of an area, we use GIS methods to register changes in land production and shifts in the system of cultivation using satellite and remotely sensed data (previous applications of this approach are presented by Costinot et al., 2016, Dell et al. 2014, Hsiang and Kopp 2018). Specifically, we use the satellite data provided by the Copernicus Global Land Service (European Union's Earth observation programme) about Gross Dry Matter Productivity (GDMP). GDMP registers the overall growth rate of the vegetation of an area and is directly related to the productive capacity of a land and changes in aggregate yields. Data is registered every 10 days at a spatial grid-resolution of around 300x300m,[3] with units customized for agro-statistical purposes.[4]

GDMP data are used to observe whether and how IFAD's interventions, by improving the welfare of a community (i.e., increasing aggregate yields), have an impact on treated communities in terms of outcomes related but not equal to IFAD's main goals. In particular, we investigate how improvements in treated areas modify the opportunity cost of joining a civil conflict and affect the presence and the intensity of conflicts.[5]

Data on conflict events are drawn from the PRIO/Uppsala Armed Conflict and Location Event (ACLED) dataset. This data source provides information about exact location, in terms of latitude and longitude (GPS coordinates), date, and additional characteristics of a wide range of conflict-related events. Civil conflict episodes are defined broadly, to include all kinds of activity. Event data are derived from a variety of sources, mainly concentrating on reports from war zones, humanitarian agencies, and research publications. The use of these data is long consolidated in the literature on conflicts (see for instance Bertoni et al. 2019, Di Maio and Tushar, 2013, Harari and La Ferrara 2018).

[3] Additional information about how GDMP is constructed and used are provided by "Copernicus Global Land Operations", at the link (last accessed: 07/01/2022):

https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_PUM_DMP300m-V1.1_I1.10.pdf.

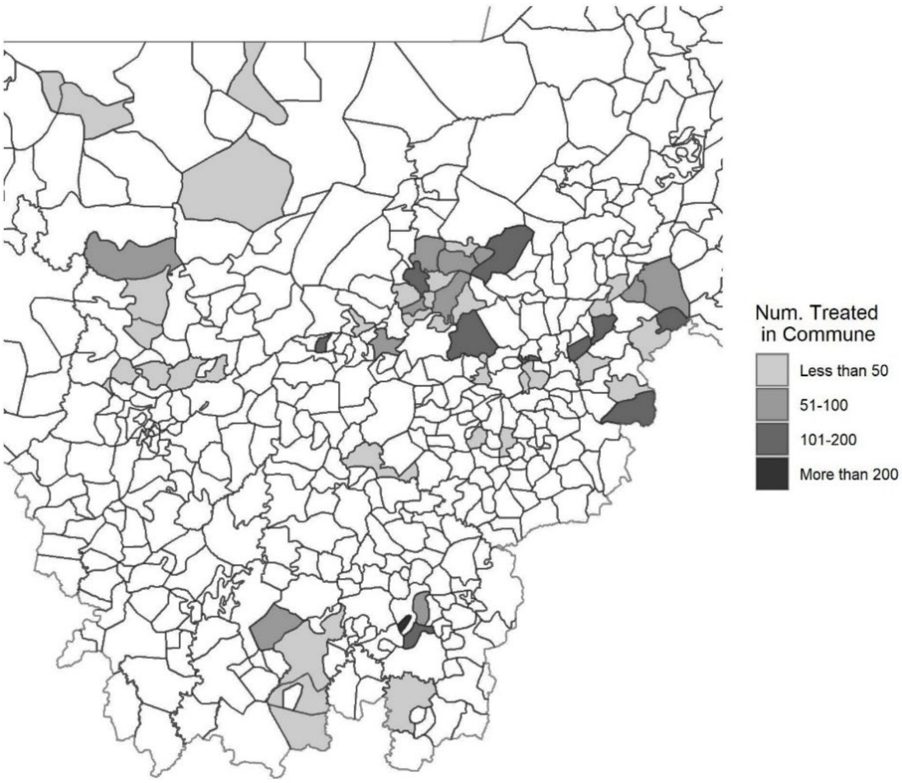
[4] Specifically, GDMP unit is kilograms of gross dry matter per hectare per day (kg/ha/day).

[5] There is a large consensus on the nexus between variation in soil productivity and the rise of civil conflicts. For a recent discussion, see Berman et al. (2021).

Case study 1: Mali

The IFAD-financed Rural Microfinance Programme (PMR) is a project that was implemented in Mali between 2010 and 2018, providing support to primarily women and youth savings and loans groups. The interventions of PMR mostly involved providing financial literacy training through the savings and loans groups and providing individual loans to group members, for rural income generating activities, most of which were invested in agricultural enterprises. We use GPS coordinates from a household survey of 1,814 households conducted as part of the IFAD impact assessment of PMR. We focus on the GPS coordinates of both the beneficiary and comparison households. For the beneficiary households the data comprise geolocations of 1,207 beneficiary households with 6,425 individuals (the treatment group). These treated individuals are identified as living in 72 villages, located in 48 Communes (geographic administrative level 3) in rural areas of Koulikoro, Segou and Sikasso regions. The specific number of treated individuals sampled for each Commune is presented in Figure 1. In the map, darker hues of color are associated to Communes with a higher number of treated individuals in the impact assessment sample, while the white color is used to indicate Communes where no individuals were involved in the project intervention (control).

Figure 1: Number of treated individuals in each Commune.



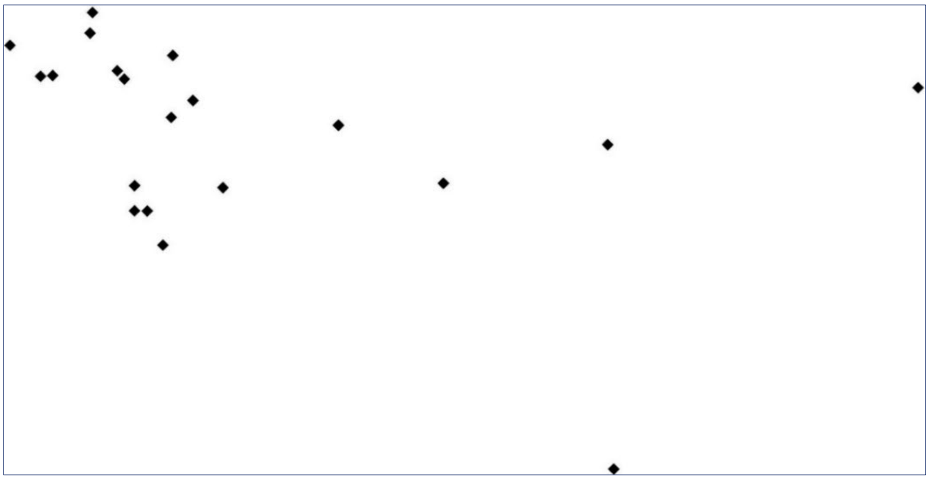
It is worth noting that, except for one case, the average per capita income of treated individuals in all Communes is below the average per capita GDP of Mali during the period in which intervention took place (2010-2018).6 This is to be expected since IFAD deliberately targets the poor and often ultra-poor and vulnerable in its rural development projects. This is shown in Figure 2, where light colored Communes indicate the presence of individuals with incomes below the national per capita GDP, and dark colored Communes registers the presence of individuals with incomes above the national per capita GDP. White colored Communes are not part of the beneficiary (treated) sample.

Figure 2: Average per capita income of treated individuals vs national per capita GDP

From the F2F interviews conducted as part of IFAD's impact assessment of PMR, we obtain the exact geolocation, in terms of latitude and longitude, of treated individuals. An instance of this data is reported in Figure 3, where each dot indicates the location of the household of the individuals treated in the village Niantanso. To comply with personal data and privacy protection guidelines, we do not reveal the village boundary nor the scale and geographic direction in Figure 3.

[6] The information about the income of treated individuals was obtained from the household survey interviews conducted as part of IFAD's impact assessment of PMR.

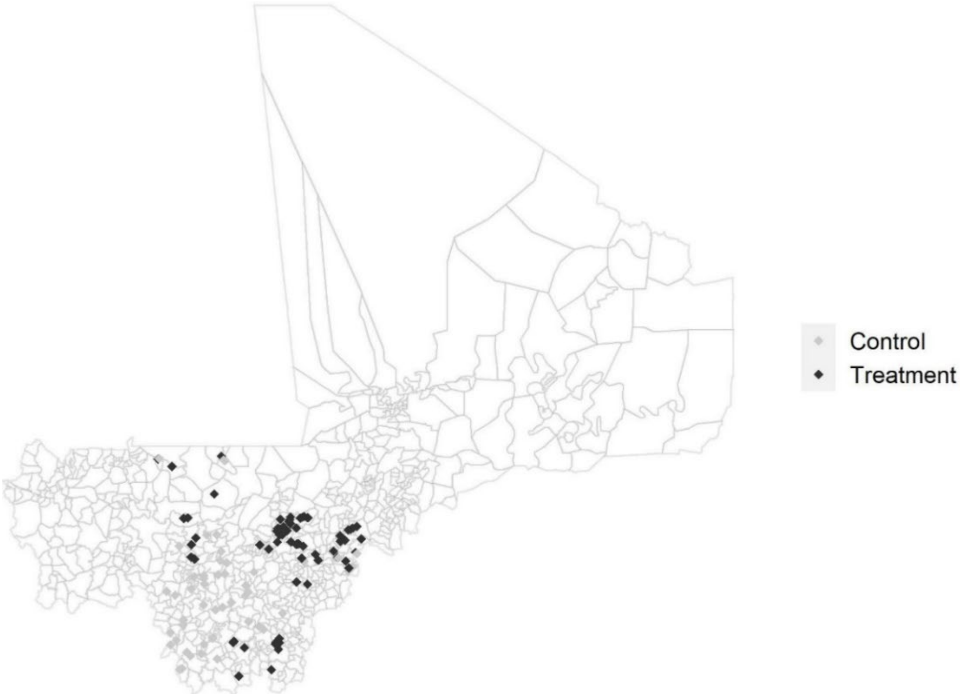
Figure 3: Household location of treated individuals in the village of Niantanso



A key feature of our data is that we have both treated and control individuals, with the latter leaving in villages different from those where the former resides. Consequently, we can work at the aggregate level by comparing villages of treated individuals with villages of control individuals.

In Figure 4, we show the exact location of treated and control villages.[7]

Figure 4: Location of treated and control villages

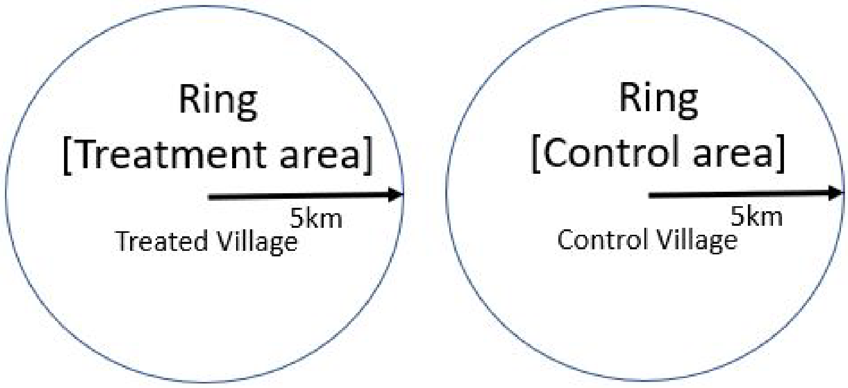


[7] The number of control villages is 49.

Data construction

We have no information about the exact boundaries of villages. However, we know the location of interviewed individuals (treatment and control). Therefore, we identify the centroid of the location of individuals residing in the same village, and we assume this to be the center of the village. We then draw a ring of 5 km radius around this point, and we consider this area our unit of analysis. The length of the radius is kept relatively large in order to account also for potential spillover effects around villages. An instance of how rings for treatment and control villages are created is provided in Figure 5.

Figure 5: Definition of treatment and control areas



In the area covered by the rings surrounding treated and control communities, we compute two metrics for all months going from June 2014 to December 2020:[8] i) the number of conflicts occurred at month *t*; ii) the average GDMP of the area in the 6 months before *t*.

Once seen as a democratic leader, Mali has become an epicenter of regional conflict and instability over the past decade. To get a sense of the on-going conflict events in Mali over the time span considered, we report the average number of conflicts registered in this country every month in Figure 6. A recent discussion on the current conflict in Mali is presented by Nomikos (2020, 2022).

Moreover, in Figure 7 we plot the average growth rate of GDMP in the Communes where treated and control villages are located. Interestingly, very small changes in GDMP are observed in these areas: i.e., the monthly average growth rate is in between -1 and 1%.

[8] We expect that treatment effects arising from the program implementation did not have an immediate impact in the area. For this reason, we focus on a time span beginning few years after the program started.

Figure 6: Average number of conflicts registered every month in Mali from 2014 to 2020

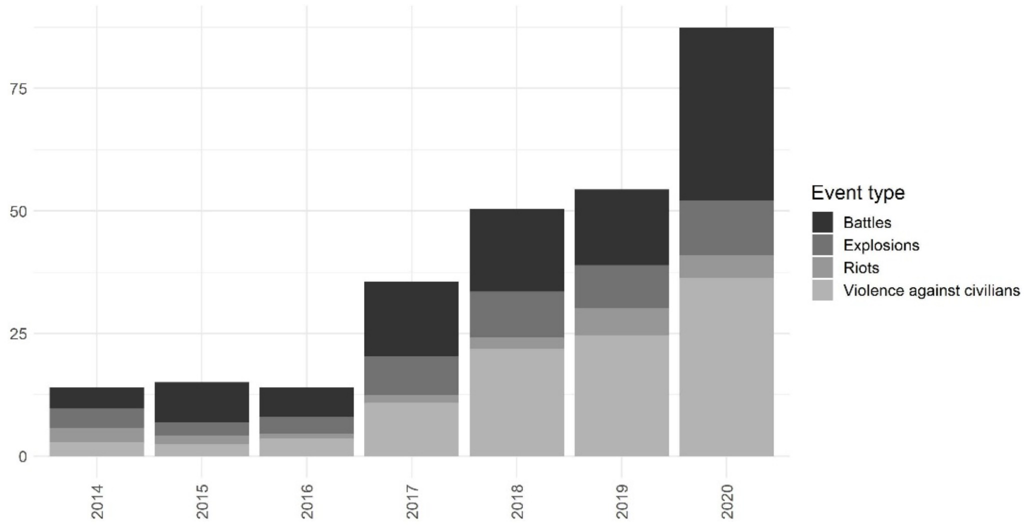
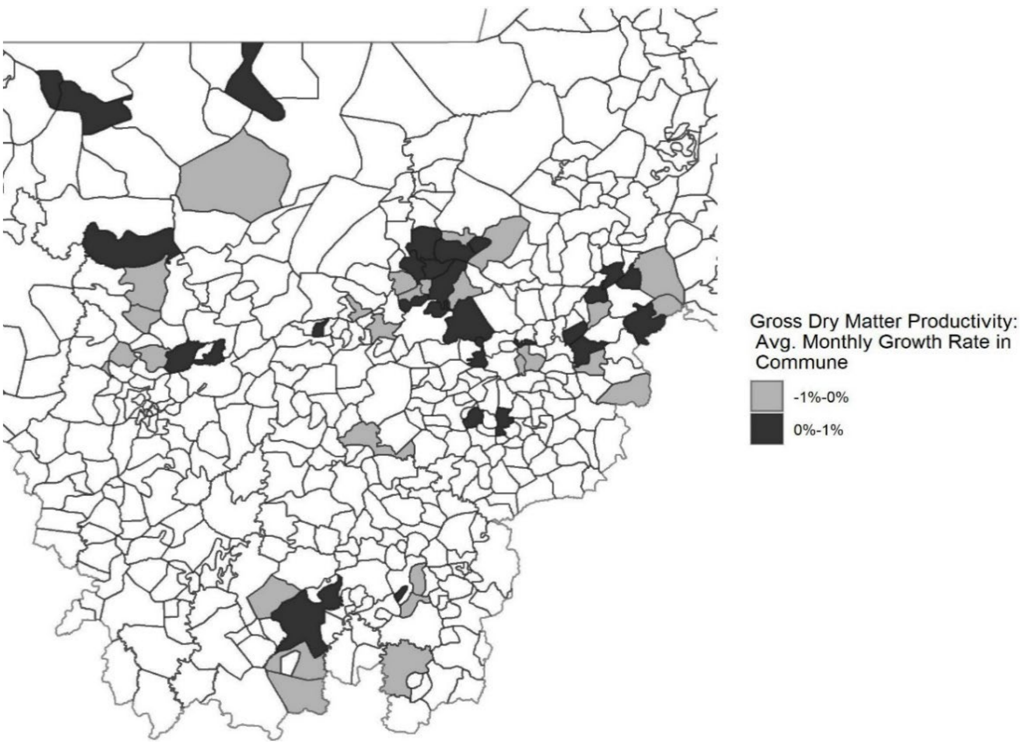


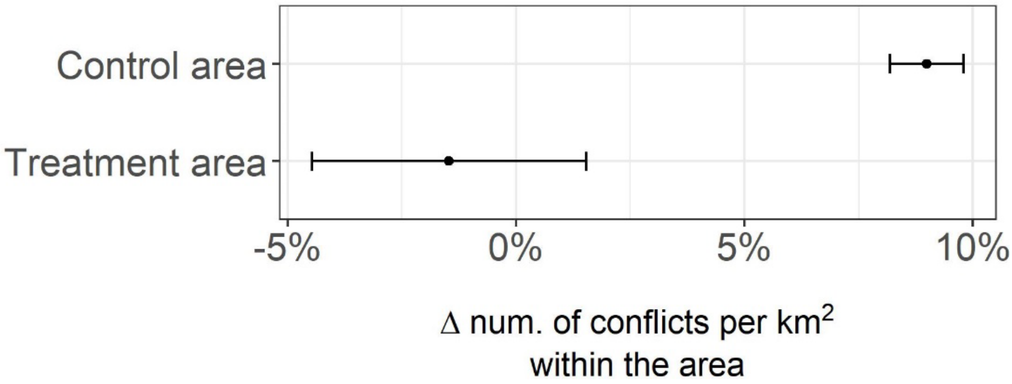
Figure 7: Average (monthly) growth rate of GDMP in treated and control areas



Empirical Analysis

We estimate the effect of an increase of GDMP in the area surrounding a village on the number of conflicts registered in the same area. To be more specific, in our model specification the dependent variable is the number of conflicts per kilometer squared in the area surrounding village *i*, at month *t*, and the regressor of interest is the average value of GDMP registered in the same area in the six months before *t*. We estimate our model using a Poisson regression (Wooldridge, 1999), which allows us to correctly account for the fact that the dependent variable, i.e., the number of conflicts, is a discrete variable, and its value can be zero in many cases (i.e., conflicts are rare events). We augment our model specification using village, month, and year fixed effects. Errors are then clustered at the village, and month-year level. The results obtained from our estimates are summarized in Figure 8.

Figure 8: Effect of a 1% increase of GDMP on conflicts in the considered area



Note: Points indicate the estimated coefficients from a Probit fixed effects model for rare events studies (Wooldridge, 1999). Lines indicate the confidence interval of a standard deviation. Model specification includes village, month and year fixed effects. Errors are clustered at the village, and month-year level.

In the figure, the dots report the estimated coefficient (point estimate) associated with an increase of 1% of GDMP on the number conflicts per kilometer squared in treated and control areas, respectively. Dark lines indicate the confidence interval of a standard deviation associated with each estimated coefficient.

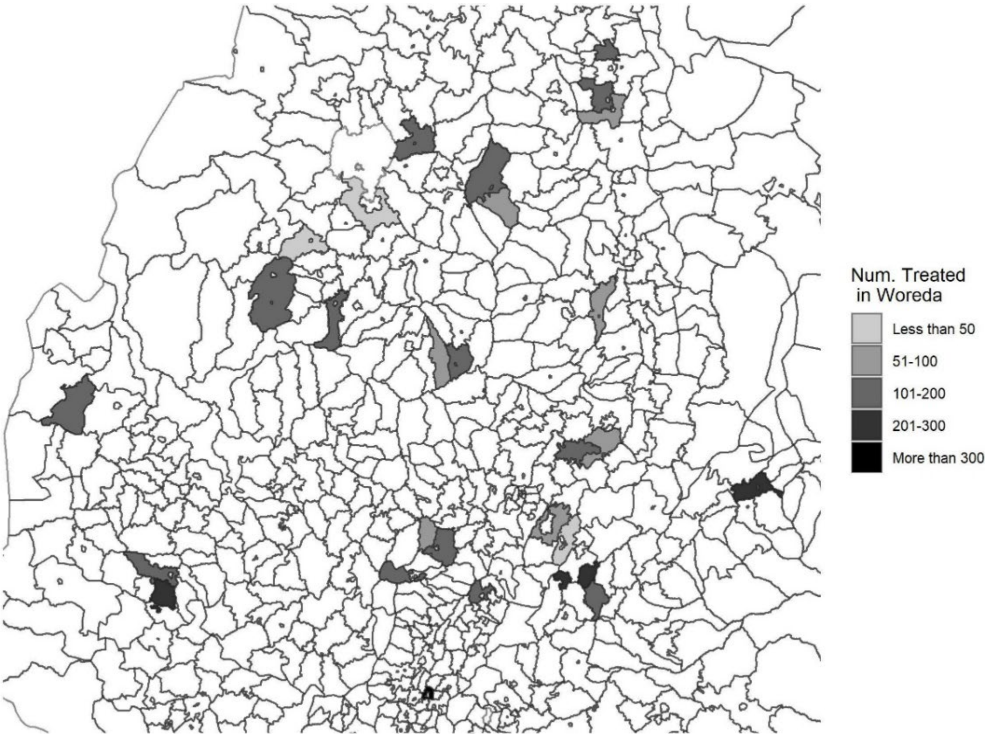
A number of interesting facts emerge from this figure. In the control areas, a 1% increase of GDMP in the previous six months, corresponds to an average increase by approximately 8% in the number of conflicts per kilometer squared during the month under analysis. Importantly, this effect of GDMP on conflicts is significantly different from zero (i.e., the value zero on the x-axis is not included in the confidence interval of the estimated effect). This result suggests that an improvement of land productivity in the control areas provides an incentive to engage in conflictual activities: i.e., the number of conflicts increases. This is consistent with the fact that small changes have been registered in the land productivity of these areas, and control individuals likely have limited opportunities to improve their welfare through agricultural activities. Hence, when GDMP increases, this may activate a fight for the new resources, and the number of conflicts rise in these areas.

In the treatment areas instead, we do not find any statistically significant correlation between an increase in GDMP and the number of conflicts. The average effect of a 1% increase of GDMP in the previous six months on the number of conflicts is not statistically different from zero (i.e., the value zero on the x-axis is included in the confidence interval of the estimated effect): i.e., the number of conflicts does not arise, on average. This is an important finding suggesting that when improvements in land productivity is managed by IFAD, the opportunity cost to engage in conflictual activities significantly decreases, and there are less chances to observe a fight for resources.

Case study 2: Ethiopia

The IFAD-financed Rural Financial Intermediation Programme II (RUFIP II) in Ethiopia, was implemented from 2012 to 2020 and entailed supporting rural financial institutions, namely Rural Savings and Credit Cooperatives (RuSACCO), unions and Micro-financial institutions (MFIs). The project was implemented as a follow-on to the original RUFIP project implemented between 2003 and 2010. RUFIP II involved strengthening the capacity of micro-financial institutions (financial services providers) and facilitating access to loans (incremental credit) for rural households for investment in income generating activities in the target communities. As part of the endline monitoring and evaluation efforts, the project conducted F2F interviews and managed to collect data from 1,559 households distributed across five regions of Ethiopia, namely Amhara, Benishangul-Gumuz, Oromia, Southern Nations Nationalities and Peoples (SNPP), and Tigray. Among the sampled households were 780 beneficiary households with 3,790 treated individuals living in 49 kebeles (villages), located in 29 Woredas (geographic administrative level 3). The specific number of treated individuals in the sample for each commune is presented in Figure 9. In the map, darker hues of color are associated to Woredas with a higher number of treated individuals, while the white color is used to indicate Woredas where no individuals were involved in the intervention.

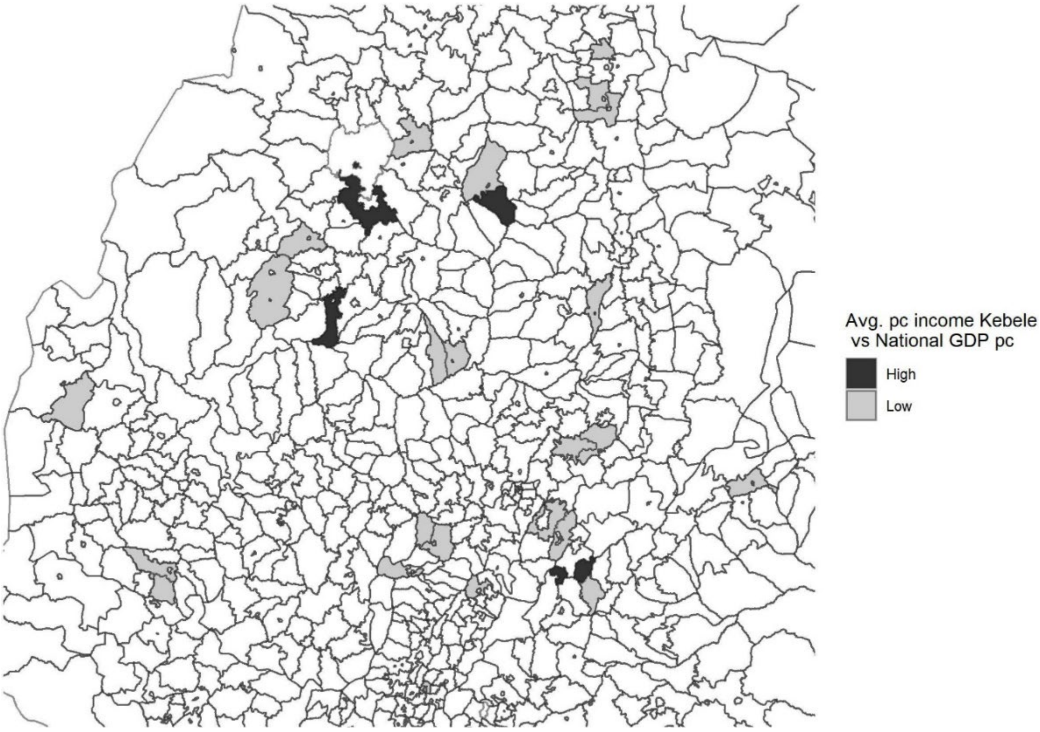
Figure 9: Number of treated individuals in each Woreda



Notably, the average per capita income of treated individuals sampled in many Woredas is below the average per capita GDP of Ethiopia during the period in which intervention took place (2012-2020).[9] This is shown in Figure 10, where light colored Woredas indicates the presence of individuals with income below the national per capita GDP, and dark colored Woredas registers the presence of individuals with income above the national per capita GDP.

From the interviews conducted as part of the endline survey, we obtained the exact geolocation, in terms of latitude and longitude, of treated and control households. An instance of this data is reported in Figure 11, where each dot indicates the location of a household with the control and treated individuals in the kebele of Aleko. Again, to comply with personal data and privacy protection guidelines, we do not reveal the boundary of the kebele nor the scale and geographic direction in Figure 11.

Figure 10: Average per capita income of treated individuals vs national per capita GDP



A notable difference exists between data collected for the impact assessment in Mali, and that collected in Ethiopia. In the former case, control and treated individuals are located in different villages whereas in the latter case, control and treated individuals live in the same kebeles. The location of the kebeles, where treated and control individuals live, is reported in Figure 12.

[9] The information about the income of treated individuals was obtained from the interviews conducted by IFAD.

Figure 11: Household location of treated and control individuals in the village of Aleko

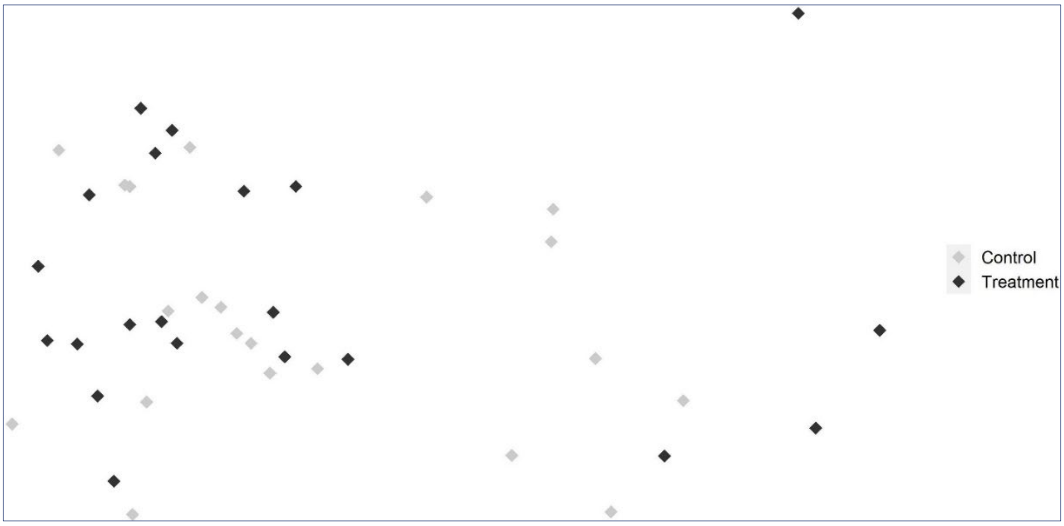
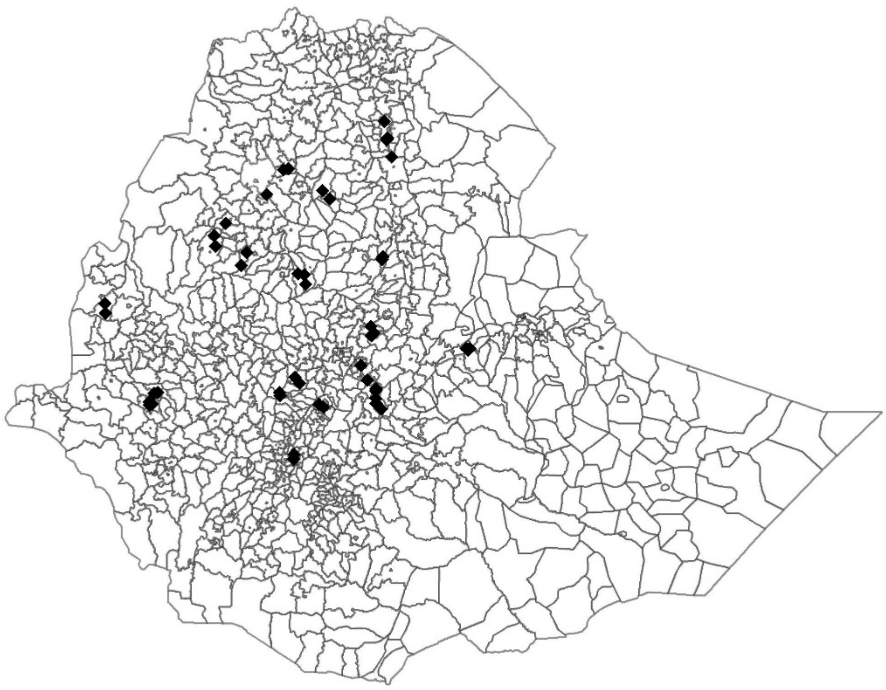


Figure 12: Location of treated kebeles

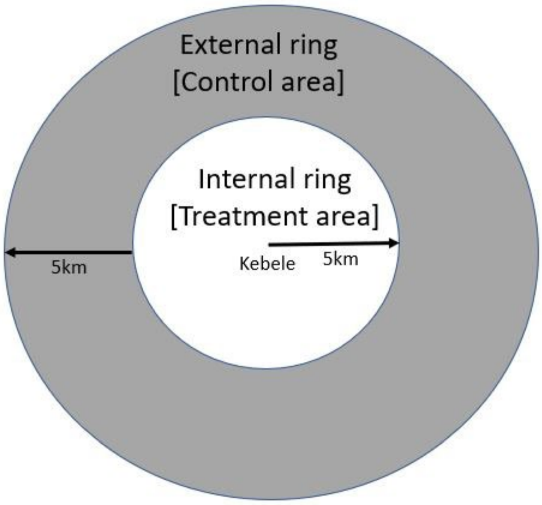


Data construction

We do not have information about the exact boundaries of the kebeles. Moreover, there are no kebeles which can be used as control areas. Therefore, we need to slightly modify the approach adopted in the previous case study (i.e., Mali).

When treatment is located at a specific point in space and a control unit is not available, a standard method of evaluating the effects of the treatment is to compare units that are close to treatment to those slightly further away (see e.g., Billings 2011; Currie et al 2015; Gibbons et al. 2005; Marcus 2021), since these are likely to share the same characteristics (and thus they are comparable). Following this approach, we define treated areas as the ring (5km radius) around the centroid of each village, and we refer to these areas as to *internal rings*. We then define control areas as the ring (5km radius) surrounding the internal ring. We refer to these areas as to *external rings*. An instance of how internal and external rings are created is provided in Figure 13.

Figure 13: Definition of treatment and control areas



In the area covered by the (internal and external) rings, we compute two metrics for all months going from June 2014 to December 2020:[10] i) the number of conflicts occurred at month t; ii) the average GDMP of the area in the 6 months before *t*.

We provide an overview of the current conflictual activities registered in Ethiopia over the time period considered in Figure 14, where we report the average number of conflicts registered in this country every month. A recent discussion about the conflict situation in Ethiopia is provided by the Institute for Peace and Security Studies (2020).

In addition, in Figure 15 we plot the average growth rate of GDMP in the Woredas where rings are located. The growth rate is always positive. Interestingly, significant improvements in GDMP are observed in many of these areas: i.e., the monthly average growth rate is larger than 5%. This is in contrast to the limited changes observed in the preceding case study of Mali.

[10] We expect that treatment effects arising from the program implementation did not have an immediate impact in the area. For this reason, we focus on a time span beginning few years after the program started.

Figure 14: Average number of conflicts registered every month in Ethiopia from 2014 to 2020

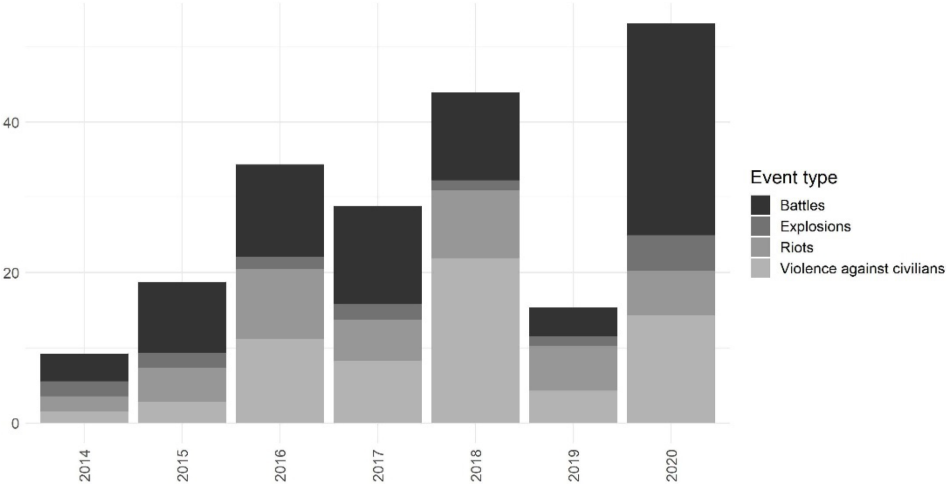
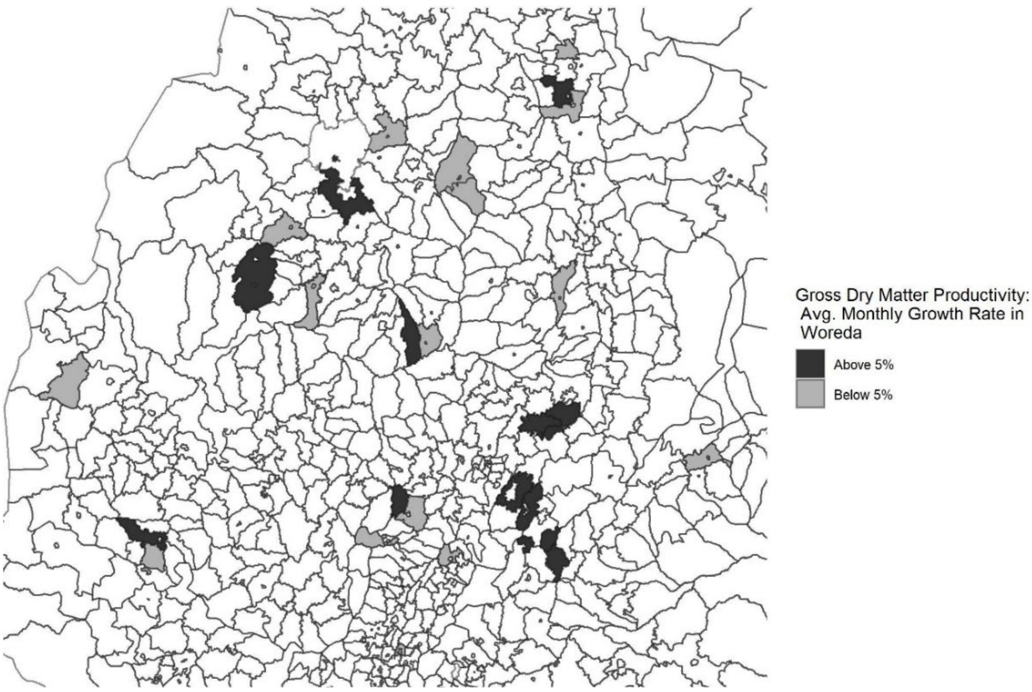


Figure 15: Average (monthly) growth rate of GDMP in rings



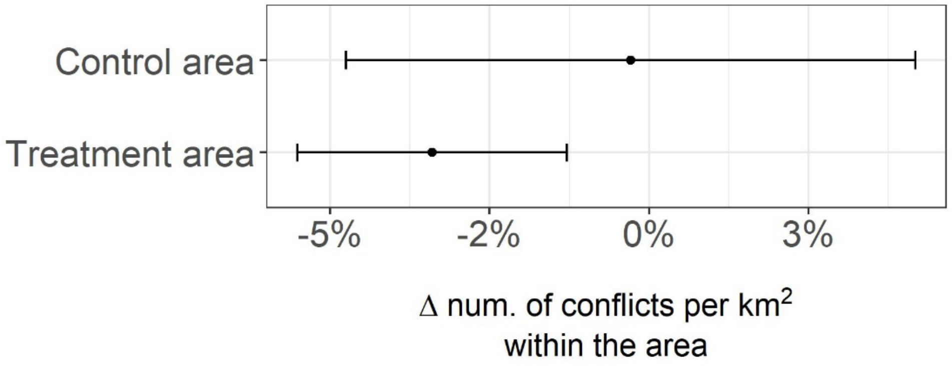
Empirical Analysis

We estimate the effect of a 1% increase of GDMP in a ring on the number of conflicts registered in the same ring. To this purpose, we use the same exact model specification adopted to investigate the data in Mali: the dependent variable is the number of conflicts per kilometer squared in the ring *i*, at month *t*, and the regressor of interest is the average value of GDMP registered in the same ring in the six months before *t*. We enrich our model specification using ring, month, and year fixed effects.

Also in this case, we estimate our model using a Poisson functional form, clustering errors at the ring, and month-year level. The results obtained from our estimates are summarized in Figure 16.

Important findings emerge from the observation of this Figure. In the control areas (i.e., the external rings), we do not find any statistically significant correlation between an increase of GDMP and the number of conflicts. The effect of a 1% increase of GDMP in the previous six months on the number of conflicts is not statistically different from zero: i.e., the number of conflicts is unaltered. This should not be surprising. With respect to Mali, where we observe small changes in GDMP, in Ethiopia we register relatively larger improvements in land productivity during the period under analysis. Therefore, an improvement in GDMP is less likely to activate a fight for new resources in these areas, and the number of conflicts does not change.

Figure 16: Effect of a 1% increase of GDMP on conflicts in the considered area (ring)



Note: Points indicate the estimated coefficients from a Probit fixed effects model for rare events studies (Wooldridge, 1999). Lines indicate the confidence interval of a standard deviation. Model specification includes ring, month and year fixed effects. Errors are clustered at the ring, and month-year level.

In the treatment areas (i.e., the internal rings), a 1% increase of GDMP in the previous six months, corresponds to an average decrease by approximately 3% in the number of conflicts per kilometer squared during the month under analysis. Hence, with respect to the program implemented in Mali, IFAD intervention in Ethiopia had a significant impact on the number of conflicts in the treated area.

Taken together, these results suggest that when we observe relatively large improvements in land productivity on average (which is the case for Ethiopia, and not for Mali), and there are smaller incentives to engage in conflictual activities in consequence of a GDMP increase, the opportunity cost to engage in conflictual activities becomes negative in the presence of the IFAD-financed project: i.e., individuals have a disincentive to participate in conflict in order to improve their economic conditions.

Conclusions

In this report, we show how GIS methods and secondary data can be used as a complementary set of tools to conduct impact assessments of IFAD-financed projects. To this purpose, we use two case studies, i.e., the IFAD projects focused on rural financial interventions in Mali and Ethiopia.

In our analysis, we study how an improvement in the welfare of a community increases in terms of aggregate land productivity, i.e., the scope of the interventions conducted by IFAD projects in these countries, is linked to the presence of conflicts in the area, an outcome related but not equal to IFAD's main goals.

In order to conduct our investigation, we used the geo-localized data of treated households to identify the areas of intervention where IFAD-financed projects were implemented. We then collect satellite data to register changes in land productivity in these areas, and combine those data with data on conflicts. Different spatial methods are adopted to identify control units to be used as a credible counterfactual to perform our GIS impact assessments.

Important findings arise from our investigation. First, we observe from the evidence obtained from Mali that when there are small chances to improve one's own welfare, as suggested by a small growth rate in land productivity, an improvement in aggregate land productivity is followed by a fight for resources: i.e., conflict increases. Importantly however, we observe that in areas where IFAD projects are present, an improvement in land productivity is not followed by a fight for resources. In other words, IFAD projects appear to be generating a buffering effect, which prevents conflicts from emerging.

Complementing this finding, we observe from the evidence obtained from Ethiopia that when land resources increase at relatively larger magnitudes, and the opportunity cost of joining conflictual activities is thus smaller, the presence of IFAD project interventions is equally important. In such cases, an improvement in land productivity is followed by a decrease in the number of conflicts, suggesting that treated household (and as a result individuals) have a disincentive to participate in conflict. This could be termed a reduction effect, as conflict events are actually reduced.

The results presented in this report, however, are not to be interpreted as an exhaustive assessment of IFAD's interventions in Mali and Ethiopia. The main aim of this report is to showcase how GIS methods can be used to complement IFAD impact assessment activities.

It is important also to stress that a number of additional analyses can be implemented with GIS methods, depending on the scope of the project under analysis. For instance, when the intervention is meant to facilitate access to an area by creating a new infrastructure such as roads, one can use GIS pathfinding methods using digital terrain models to determine the change in travel time caused by the intervention and determine the improvement in the market access of a population (see for an application Burgess et al. 2015 and Faber 2014). In other cases, when the intervention is implemented to improve crop production during the dry season, e.g. through irrigation of an area, one can use Normalized difference vegetation indexes (NDVI) to register changes in green vegetation and obtain a reliable measure of the benefits to the population living in the targeted area (this is for instance studied in Bustos et al. 2016, Dell et al. 2014, Hsiang and Kopp 2018).

Moreover, the integration of GIS data with spatial statistics techniques can also allow to estimate the spillover effects of IFAD's programs on surrounding areas. That is, it can be possible to assess the effect of the program on areas that did not directly receive the project interventions. The calculation of such an externality is paramount for the design of inclusive policy interventions that do no harm. A given target impact can be indeed achieved by treating a different number of units depending on the magnitude of the spillover effect, the so-called spatial or social multiplier (Arduini, Patacchini and Rainone, 2019).

In conclusion, the combination of IFAD GPS location data collected during impact assessment surveys and satellite data offer a valuable contribution to complement and further corroborate IFAD assessment results.

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