Integrating GIS and Remote Sensing

in Impact Assessment of Rural Development Programs

A technical note

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RESEARCH AND IMPACT

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A technical note[1]

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Introduction

The use of GIS and remote sensing approaches in empirical economic research has been growing in recent years. Rural development studies are increasingly taking advantage of the growing amounts of geospatial data and satellite imagery that are now available, many through open access (e.g. from the European Space Agency and the National Aeronautics and Space Administration (NASA)). The use of geospatial data can vary from the basic use of maps to visualize study areas or presentation of descriptive statistics in a geospatial manner, to the more advanced use of geospatial variables in statistical and econometric analyses (BenYishay et al. 2017). Geospatial data also offer the possibility of more accurate measurement of variables with a geospatial dimension, for example the measurement of farm land area or distances to cities and infrastructure (Lobell et al. 2019; Banerjee et al. 2020). More recently, advances in the application of artificial intelligence on satellite imagery is opening new areas of research that allow for identification of crops and improved estimation of crop yields (Tiedeman et al. 2022; Constenla-Villoslada et al. 2022) as well as assessment of economic welfare (Yeh et al. 2020).

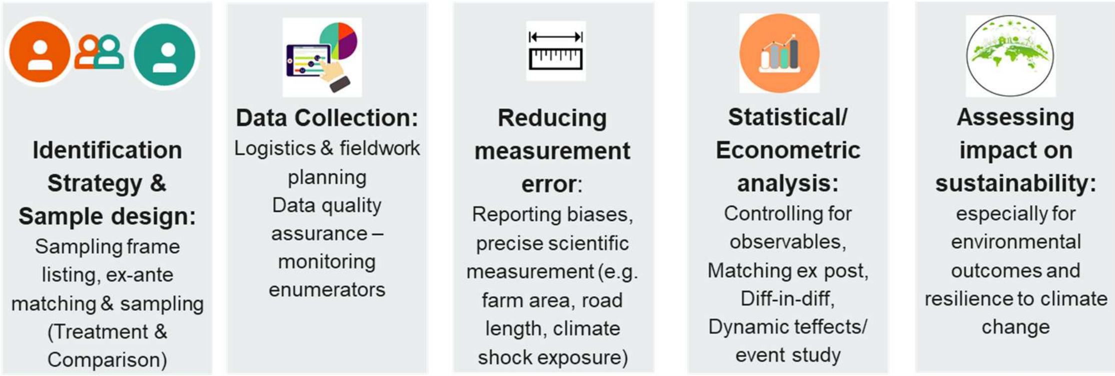
In the case of impact assessments of rural development programs, the use of geospatial data is also on the rise. Often GIS is used to complement traditional methodologies that rely on household interview surveys combined with qualitative methods that collect data through focus group discussions and key informant interviews. A fundamental aspect of leveraging GIS in impact assessments is georeferencing units of observation, such as households and communities, during survey data collection. This allows to generate geospatial descriptive statistics of the study sample but also to extract remote sensing data from various sources for use in more advanced statistical and econometric estimations, for causal inference. This latter aspect presents a tremendous opportunity to vastly improve methodologies for impact assessment and is the focus of this note.

Unlike standard population studies that aim to generate statistics about the population using a representative sample, impact assessments have the additional challenge of ascribing attribution of observed impacts. This challenge is at the core of conducting rigorous impact assessments and in specific areas, GIS and remote sensing approaches offer a hand at arriving at rigour. The entry points for GIS to enhance rigour in impact assessments of rural development programs are described in this report along with the various limitations that must be taken into account when considering the use of GIS in impact assessments.

Where and how to integrate GIS in Impact Assessments

There are several ways that GIS and remote sensing can be integrated into impact assessment workflows to add value and improve rigour. Figure 1 below shows some of the key entry points where GIS and remote sensing approaches can be applied to enhance the traditional or standard approach to conducting impact assessments. Some aspects are of practical importance in the sense that they support the process of conducting an impact assessment and simply provide convenience; for instance the use of GIS to locate sampled households. Others offer methodological advantages that help improve the rigour of analyses be it through improved measurement (thus reducing or eliminating measurement error) or through cleaner identification strategies that enable attribution of impacts to the specific interventions being assessed.

Figure 1. Entry points for integrating GIS in impact assessments



Source: Authors' representation

Sample design and matching variables

In the case of ex-post impact assessments conducted by IFAD, GIS is used at the onset as part of the appropriate identification strategy and corresponding sample design. GIS can be used to delineate the sampling frame, first at the village or community level based on monitoring and evaluation records of the rural development projects to be assessed. Where the project monitoring and evaluation data consist of GPS coordinates or other geospatial data beyond the administrative levels (villages), more precise delineation of the sampling frame can be done on the basis of GIS. Usually such data do not exist and a listing exercise is often required, and this too can be guided by GIS at the very least from a logistical and practical fieldwork point of view.

When the locations of households or communities where the program interventions took place are known prior to data collection, sampling can then be informed by remote sensing data in conjunction with census data (both population and agricultural). Geospatial characteristics of the villages can be extracted from various databases to facilitate statistical matching. Other secondary data that may be available at the community level may also be used for matching in addition to demographic remote sensing data on population density.

Given the information on the full list of villages/communities where the project was implemented, ex-ante propensity score matching can be conducted using the remote sensing data at baseline (i.e. as measured before project implementation), to find close-match villages/communities. In this way, communities that did not receive the project interventions but had very similar characteristics with those that did, at baseline, can be considered for potential inclusion as the control group.

Based on information in the design documents and actual roll out of the project interventions, the criteria for selecting beneficiary locations and ultimately households are assessed. Where some of the criteria have geospatial characteristics, for example villages that are adjacent to the coast or villages that are in mountainous terrain, these geospatial characteristics can then be included as matching variables. Several examples of this approach can be found in IFAD's impact assessments. For example the IA of the Post-Tsunami Sustainable Livelihoods Programme (PTSLP) in Tamil Nadu, India selected fish-vending women and self-help groups in villages (panchayats) that were close to the coast, as this was a critical targeting criteria, since the project had been implemented to support fishing hamlets that had been affected by the 2004 tsunami (Mabiso et al 2021).

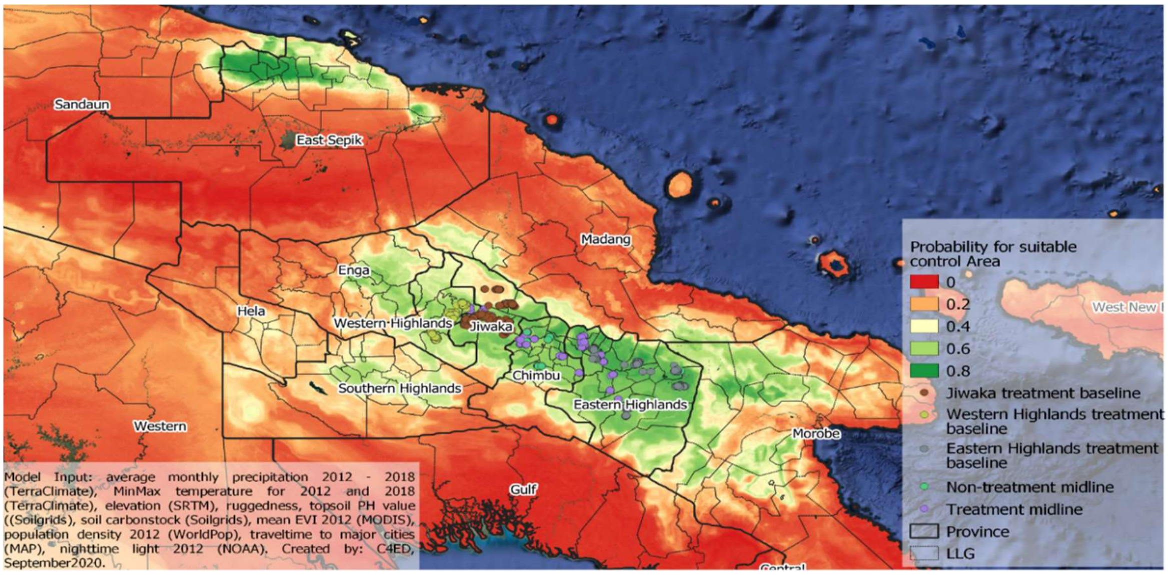
Similarly, in the Second Cordillera Highland Agricultural Resource Management Project (CHARMP2), households located in mountainous/upland and landlocked areas of the Cordillera Administrative Region in northern Philippines were selected to receive benefits from the project. As such the control villages (barangays) were chosen on the basis of being in similar geographic terrain and possessing similar characteristics (Hossain et al. 2022; 2021). Furthermore, when propensity score matching was performed, ex ante, using remote sensing data on variables such as rainfall, temperature, altitude, etc. significant common support was established at the village level.

Figure 2. Geospatial listing and sampling of control villages and households in the Philippines CHARM2 project impact assessment

Source: Hossain et al. (2021)

In the case of IFAD projects some of these geospatial data are collected by the M&E teams of the projects and can be useful to the design of the impact assessment. In the case of an IFAD-supported project, georeferenced data on market road infrastructure were collected in Papua New Guinea for the IFAD-financed Productive Partnerships in Agriculture project. Such data were useful for designing part of the impact assessment that sought to assess the effects of road infrastructure interventions and random forest approaches were applied on the satellite imagery to select control areas. Figure 3, below shows a map of locations that were sampled to measure the impact of the road infrastructure invested by the project (Richert et al. 2022)

Figure 3. Random forest predictions (machine learning) for suitable coffee control areas for the PPAP project IA in Papua New Guinea



Source: Richert et al. (2022)

Data collection and geo-referencing

Most of the uses of GIS and remote sensing approaches in fieldwork or data collection, serve practical purposes. One example is the use of GPS devices in the field to locate sampled villages and households in support of enumerators and supervisors of data collection teams. In this regard, GIS is used as a way of planning logistics in the field to create efficiencies for field teams and potentially reduce costs of undertaking surveys. In addition, it can serve the purpose of monitoring data collection activities and ensuring that the interviewers do actually visit the sampled locations and are conducting data collection in line with fieldwork protocols.

An important aspect of data collection is the actual georeferencing of households and where feasible, the georeferencing of farms (fields) and infrastructure such as roads, bridges, market places and processing facilities that the projects would have invested in. As standard practice, enumerators involved in collecting survey data for IFAD impact assessments collect GPS coordinates of the households during interviews using tablets or specialized GPS devices. Similarly, the GPS coordinates of the locations where the community survey take place are collected.

Identification strategies and econometric analysis

While most of the IFAD impact assessments rely on ex-post household and community level data with the use of statistical matching techniques as the workhorse identification strategy, several other identification strategies can be used depending on the research question, setting and available data.

In the case of assessing program effect on environmental outcomes such as land use and land cover (e.g. forest land cover), remote sensing can provide time series or panel data on outcome variables of interest. Given that earth observation data are of a time series nature, they offer the ability to measure changes over time. This can then allow for the use of difference-in-differences estimators or other panel data methods. An example, where remote sensing data were used for the outcome variable, is found in the IFAD impact assessment of the Community-based Forestry Development Project in Southern States (DECOFOS) in Mexico. Here, one of the key interventions entailed supporting reforestation and agroforestry efforts at community levels. Using NDVI as an outcome variable, the authors of the impact assessment find that the project significantly increased levels of NDVI (Cavatassi et al. 2018). Event study and dynamic treatment effects models can also potentially be applied to settings where remote sensing data linked to project and non-project locations offer the opportunity to construct panel (longitudinal) data. Ideally, when baseline and midline data on socio-economic variables are also collected for the same geographic units of observations or households clustered within the geographic units, then richer analyses can be conducted using endline data to uncover the link between variables at the community/spatial level and those occurring at the household level.

It is conceivable that in ex ante impact assessments, GIS can also be used as part of targeting and potentially implementing a ***geospatial-cluster randomized control trial,*** where treatment assignment is randomized across geospatial units. If comprehensive geospatial data are used as part of the project design and targeting criteria, once areas that meet the inclusion criteria have been identified, deployment of program interventions could then be assigned randomly among the eligible geographic locations. In this manner, a randomized control trail could effectively be implemented with a cluster design. Of course, actions would be needed to ensure compliance and that there are no contamination or spillover effects occurring in the control geographic areas. Testing the differences in geospatial variables including those from remote sensing databases for the clusters could be performed as part of the descriptive analysis in such a design. While this approach is certainly attractive from the point of view of rigour, it is not always feasible given the complexity of project implementation; hence it is yet to be implemented as part of IFAD impact assessments.

Where spatial-temporal roll out of the interventions is phased and georeferenced or mapped precisely, GIS offers the possibility of using an ***event study design*** as an identification strategy. ***Geospatial regression discontinuity design*** is another identification strategy that could be used in an impact assessment. Here, several studies have been carried out elsewhere using a variety of approaches to create a geospatial running variable where a geospatial cut-off that determines treatment assignment can be established. Jones et al (2022) implement a geospatial RD identification strategy to measure the effect of irrigating plots in Rwanda and how factor market failures limit adoption of irrigation. ***Geospatial fixed effects*** is also an option, which Jones et al (2022) also use in the same paper that implements the geospatial RD. In many cases, where geospatial data provide a panel dataset, most economists have applied fixed-effects regressions using the remote sensing based variables as outcome variables and/or control variables. Based on the GPS coordinates data linked to geo-located conflict data from the ACLED database, Mabiso et al. (2022) estimate geospatial fixed-effects models to ascertain the conditional correlation between placement of IFAD rural financial services projects and conflict outcomes at village level in Ethiopia and Mali.

Geospatial instrumental variables (IV) is another identification strategy that may be used to estimate attributable impact of a rural development project. In this case, establishing a valid geospatial instrument will need to meet the standard requirements of an instrument in an IV or control function approach to estimating the impact.

Climatic variables

A number of climatic variables influence development outcomes and have to be controlled for in regressions that estimate the impacts of program interventions. This is particularly the case when the outcomes of interest are directly linked to climatic variables, for instance crop production or livestock production that is dependent on natural rainfall (rain-fed agriculture) and can be exposed to climatic shocks. Some of the key variables that have been included in IFAD impact assessments include precipitation (or rainfall), temperature, wind speed, saline intrusion, and sea level. Occurrence of flooding and drought as measured by drought indices (e.g. the standardized precipitation index (SPI)) are additional climatic variables derived from remote sensing databases that could be used. Other geospatial data that might not qualify to be called climatic variables but are still linked to climatic conditions include altitude or elevation, distance to water bodies and mangrove cover. These variables can have great bearing on development outcomes of interest and as such would need to be controlled for during data analysis.

An important consideration is on how remote sensed data on climate can be incorporated in impact assessments and the relevant data source. In an analysis of the effects of rainfall on crop production, rainfall data from different sources were incorporated by McCarthy et al (2021a;b). Analyses show that different sources can lead to different results even when the method of analysis is identical. Alfani et al (2021) also use climatic variables from remote sensing databases to assess the effect of the El Nino on adoption of climate adaptation practices in Zambia. Use of remote sensing data in this regard reveal very important insights for interventions focused on climate adaptation practices.

Another important consideration is the specific type of variable to include in the analysis. In a study to assess the impact of climatic variables on crop production, McCarthy et al (2021a) include the mean and coefficient of variation of rainfall over a 12-month period and during the growing season but also during the plant flowering period as well as the onset period of the rains. They find that use of key variables linked to these agronomic aspects of the crop in question is an important consideration when choosing the type of variable to include. Another example of an important agronomic consideration is whether the crop analyzed is a seasonal or perennial crop. Crops such as coffee or cocoa, which grow over several years before bearing fruit would likely be influenced by rainfall taking place over a longer period of time.

Other than using climatic variables to understand agricultural production, climatic variables can be useful to beterr understand households' exposure to specific climatic shocks as well as their climate resilience or ability to recover from such shocks. In the case of droughts, floods, cyclones, saline intrusion and wild fires, remote sensing can provide objective measures that can be obtained from relevant data sources for use in statistical and econometric analyses. In the IFAD impact assessment of the Project for Adaption to Climate Change in the Mekong Delta in Ben Tre and Tra Vinh Provinces in Vietnam, geospatial data on saline intrusion were included to control for their effects on crop production, particularly rice production. Assessment of resilience to saline intrusion has also been done by incorporating the geospatial data on saline intrusion.

Proxy variables

In some cases collecting data on key outcome indicators might not be possible. For example during the period of travel restrictions or in context affected by conflict, it may be possible to use remote sensing data to generate proxy variables that are known to be correlated with the outcome variables of interest. Using these variables can still provide insights into the impact of the projects even when primary data collection is not feasible.

Infrastructure such as roads, buildings (settlements) and irrigation canals can be observed through satellite imagery. In cases where the rural development project involves building or rehabilitating such infrastructures, GIS approaches can be used to assess the baseline conditions but also to verify if treatment has occurred. Market infrastructure that are georeferenced can also allow for the computation of travel times between farms or farm households and the respective markets, providing an alternative estimate of beneficial market access, which is IFAD's second Strategic Objective (SO2). In a sense travel time to markets or existence of the road infrastructure can serve as a good proxy for market access (Nelson et al. 2019).

In the case of the Ethiopia and Mali impact assessment conducted by IFAD, additional analysis was carried out to begin assessing conditional correlations between program interventions and conflict events (Mabiso et al 2022). Constenla-Villoslada et al (2022) use satellite-derived data on enhanced vegetation index EVI) and gross dry matter productivity (GOSIF-GPP) as a proxies for land productivity and use quasi-experimental impact evaluation methods to examine the impacts of the Sustainable Land Management Project in Ethiopia .Yeh et al (2020) also show promising approaches to estimating economic well-being in Africa using deep learning techniques. Such proxy indicators can then serve as outcome variables where the treatment effects can be estimated upon. Table 1 below shows a list of potential proxy outcome indicators that have been considered for assessing impacts. While several may be useable, it is important to recognize the limitations of proxy variables that might seem to be good candidates at first sight. For example, while night lights data have been used by economists as a proxy for economic well-being, this indicator often performs poorly in rural settings, making it less useful for assessing impacts of rural development projects.

Table 1. Potential GIS data that can be used as proxy variables or indicators in Impact Assessments

GOAL/SO	RMF INDICATOR	PROXY GIS DATA AND DESCRIPTION	POTENTIAL LIMITATIONS	WEB LINKS (Resources)
GOAL	2.1.1	Global gridded economic data are very scarce. Kummu et al. (2020) prepared annual gridded datasets for GDP per capita (PPP), total GDP (PPP), and HDI, for the whole world at 5 arc-minutes (10 km at equator) resolution for the 25-year period of 1990–2015. Additionally, total GDP (PPP) is provided with 30 arc-sec resolution for three time steps (1990, 2000, 2015). Steele et al. (2017) combine mobile data and georeferenced data in Bangladesh to estimate poverty. This approach employs proprietary cell phone data merged with georeferenced data.	Not available for more recent years that correspond to the impact assessment years. Cell phone data not easily accessible. Only done in the case of Bangladesh but potentially provides a methodology for use in other countries.	https://datadryad.org/stash/dataset/doi:10.5061/dryad.dk1j0 Mapping poverty using mobile phone and satellite data | Journal of The Royal Society Interface (royalsocietypublishing.org)
		Use of night lights data as a proxy to estimate poverty has been implemented in some countries. This tends to work for urban areas. World Bank has developed the Light Every Night Database which provides open access to all nightly imagery and data from the Visible Infrared Imaging Radiometer Suite Day-Night Band (VIIRS DNB) from 2012-2020 and the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) from 1992-2013.	A study by Heitmann and Buri (2019) still finds "that remote sensing and geospatial boosting approaches can be used to improve efficiency and optimization for traditional household survey methods. However, significant work remains before remote sensing models can fully replace ground-based surveys." Levin et al (2020) provide a review of the uses of night lights data, including the prospects for use in socioeconomic analyses.	https://www.earthdata.nasa.gov/learn/backgrounders/nighttime-lights https://registry.opendata.aws/wb-light-every-night/
SO1: PRODUCTIVE CAPACITY	2.1.2	Normalized Difference Vegetation Index (NDVI) & Enhanced Vegetation Index (EVI): These indices measure vegetation cover using satellite imagery from MODIS that greatly improves scientists' ability to measure plant growth on a global scale. EVI is similar to NDVI, it corrects for some distortions in the reflected light caused by the particles in the air as well as the ground cover below the vegetation. Increasingly used as agricultural production potential, also in RDR2019. Coverage: 1981-present, Resolution: 1-10kms.	Vegetation indices are only a measure of greenery observed on the land, thus they cannot be a proxy measure of any other form of production besides agricultural production potential (mainly crop and tree production). Also, clouds and aerosols can often block the satellites' view of the surface entirely, glare from the sun can saturate certain pixels, and temporary malfunctions in the satellite instruments themselves can distort an image. Seems to stop in 2016? Can only be a proxy indicator of ag productivity as how soil OM contributes to ag productivity heavily depends on inputs, management practices and climate	https://lpdaac.usgs.gov/products/mod13q1v006/ DOI: 10.5067/MODIS/MOD13Q1.006
		Gross Dry Matter Productivity (GDMP) GOSIF-GPP and other Solar-induced chlorophyll fluorescence (SIF) products	These are more recently used as they are more correlated with crop production. However, there additional ground-truth analytical work is still ongoing.	https://land.copernicus.eu/global/products/dmp https://globalecology.unh.edu/data/GOSIF.html
		Soil Organic Matter: Soil organic matter is generally associated with higher crop yields and greater soil moisture retention, thus making areas with higher soil organic matter more resilient to climate variability and change. Time coverage: 1905-2016 Resolution: 1 km	The data are only available up until 2016. They can only serve as a partial proxy indicator of agricultural productivity with respect to how soil organic matter contributes to agricultural productivity. However, agricultural productivity heavily depends on inputs, management practices and climate.	www.isric.org https://www.soilgrids.org/

GOAL/SO	RMF INDICATOR	PROXY GIS DATA AND DESCRIPTION	POTENTIAL LIMITATIONS	WEB LINKS (Resources)
SO2: BENEFICIAL MARKET ACCESS	2.1.3	Travel time to nearest urban market (densely populated area): Continuous index based on travel time to nearest urban centre with 50,000 inhabitants, also used as adaptive capacity indicator in IFAD vulnerability maps. After identifying community/household locations, these data can be used as indicators of community/household level URBAN market access. Coverage: 2015 Resolution: 1km	It is a proxy of markets, as it only measures urban centres not markets, and cannot account for the more important rural, semi-rural and peri-urban markets. Settlements >50,000 were used, however the raw data can be re-processed to change settlement size (smallest possible 5,000 people).	See: https://www.nature.com/articles/s41597-019-0265-5
SO3: CLIMATE RESILIENCE	2.1.4	Climate and extreme weather variables used to verify climatic shock: Floods Cyclones Fires (VIIRS NASA data – 375m resolution) Count data on fires incidence Burned area (square meters) Land Cover Land Use data can be used in estimating carbon sequestration	Most datasets have different timeframes and frequency of observation, making it difficult to pool all of them in the same analysis. Different levels of resolution of satellite imagery also affect how one can used the data through collapsing/aggregating at higher levels.	Cyclones and storms: https://apps.ecmwf.int/webapps/opencharts/?facets=%7B%22Product%20type%22%3A%5B%5D%2C%22Range%22%3A%5B%5D%2C%22Parameters%22%3A%5B%22Tropical%20cyclones%22%5D%7D https://www.earthdata.nasa.gov/learn/find-data/near-real-time/firms/viirs-i-band-375-m-active-fire-data https://www.nature.com/articles/s41597-022-01307-4
OTHER IMPORTANT INDICATORS: **CONFLICT** **POPULATION DENSITY**	-	Conflict events can be measured using the Armed Conflict Location and Event Data (ACLED) Population density from Worldpop (30 arc-second resolution) from 2000-2020 Meta (Facebook) also has available socio-demographic data on population density computed at high resolution	ACLED data are based on reported incidences of conflict, which are geo-referenced. Classification of conflict events may be important consider, as some conflicts are exogenous while others are endogenous depending on the kind of analysis carried out. Relatively lower resolution Still new and untested for applications in impact assessment	https://acleddata.com/#/dashboard https://hub.worldpop.org/project/categories?id=18 https://dataforgood.facebook.com/dfg/tools/high-resolution-population-density-maps

Note: The feasibility of using the indicators above for IAs of IFAD projects depends on the resolution and time variation of indices. This is because impact can be estimated as the difference in differences between treatment and control areas (preferably communities/villages) before & after the project. Given that average projects last for 6-8 years, but activities usually take two years to kick start, we would need indicators that can be reasonably expected to change over a 5-year period in line with projects' duration. Therefore indicators that are only available for one year and those that do not change significantly over time (even if data are available) may not be of use for the purposes of impact assessment.

Conclusion

This note sought to summarize some of the GIS and remote sensing methods that can be integrated into impact assessments of rural development projects. Highlights include the increased applicability of GIS and remote sensing in impact assessments but also the limitations that need to be carefully considered when exploring the use of GIS and remote sensing for impact assessment.

What is clear is that GIS and remote sensing do not replace traditional survey methodologies but rather are complements that can richly enhance the rigour of the impact assessments while providing convenience and practical support for fieldwork and data collection activities.

Of note is that remote sensing is applicable to specific variables and methodological approaches. For example, climatic and environmental variables that are observable through satellite imagery readily lend themselves for use in impact assessments, especially when the program interventions are focused on addressing issues of the environment or climate. Examples noted include the IFAD projects focused on reforestation and agroforestry as well as projects that address issues of land degradation, including climate adaptation interventions such as terracing, and other soil erosion control measures.

The inclusion of climatic variables such as precipitation, temperature, wind speed, sea level rise and saline intrusion reveal the heterogeneity of the type of variables that should be included in the analysis when conducting impact assessments. Moreover, within the same variable domain, it is not always straightforward which specific variable or transformation of the variable one should include for analysis. Recent work by the team of McCarthy et al (forthcoming) as well as previous work by Arslan et al (2017) show that simply including means (the average) or not considering the timeframe and frequency of the variables to include, may be inadequate for causal inference. Instead, most studies include the coefficient of variation as well as the mean and consider both short-term as well as long-term (e.g. 30 years of data). Most of the data are also observed on a dekadal basis (every ten days). In the case of temperature data, thresholds are also often set. For example temperatures above 30 degrees Celsius to indicate extreme temperature. An important consideration in all these permutations of the variables included in the analyses is the theory of change and how these climatic variables are expected to affect the outcome variables of interest. Drawing from agronomic studies or in the case of fisheries projects, fisheries literature, McCarthy et al. (forthcoming) shows that grounding the variable selection on the basis of science is one important avenue for addressing the challenges of variable selection. The danger of course, is using a variety of variables in the quest of finding statistically significant results (sometimes referred to as “p-hacking”). As such it is crucial to be guided by the theory of change and interdisciplinary science in making the selection of variables.

A separate and perhaps more less tenuous challenge pertains to inconsistencies that may be found in the remote sensing data from different sources. Here the challenge requires ground truth data, where possible, combined with further testing to better understand the data sources and what may need to be done when there are inconsistencies. The advent of higher resolution satellite imagery data and the increased use of machine learning or artificial intelligence to process these remote sensing data, possibly offer new opportunities for addressing these challenges. Overall, GIS and remote sensing is not a panacea but is definitely an important tool among many in a tool box for impact assessments of rural development projects. Further refinements on the use of GIS and remote sensing in impact assessments are warranted, proceeding cautiously mindful of the limitations that do exist.

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