International Journal of Geospatial and Environmental Research

Volume 5
Number 2 *New Data for Geospatial Research*

Article 3

10-2018

Improving International Development Evaluation through Geospatial Data and Analysis

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Abstract
Increasing availability of new types of data strengthens geospatial research in different scientific fields and opens up opportunities to better measure results and evaluate the impacts of development interventions. This article presents examples where geospatial approaches have been applied in evaluations and thus demonstrate the potential use in informing policy design through scientifically sound evidence as well as learning.

The authors illustrate innovative ways of employing geospatial data and analysis in impact evaluations of international development cooperation. These interventions are concerned with topics such as biodiversity conservation, land degradation, sustainable use of natural resources, and disaster risk management. Recent methodological developments in the field of remote sensing and machine learning show significant potential to transform the vast body of new data into meaningful evidence aimed to improve policy and program design. The application and potential of methods are discussed in light of increasing importance of concerns over global climate change and climate change adaptation.

The authors call for enhancing mutual interaction between the geospatial research disciplines and the development evaluation community to jointly contribute to finding solutions for tackling pressing social and environmental challenges.

Keywords
geospatial data, evaluation, policy impact, program improvement

Acknowledgements
We would like to express our gratitude to three anonymous reviewers for their helpful critique and advice on the manuscript of the paper.

1 INTRODUCTION

While populist politics are on the rise, the growth in demand for public accountability by an increasingly critical and well-informed public exerts substantial pressure on policy-makers. Scarce financial resources are driving public policy to embrace measures that will help ensure effective and efficient policy-making. In the competition for scarce financial resources, it is thus not surprising that governments and international development institutions are under pressure to prove allocation efficiency and, in particular, to ensure and demonstrate the impacts of the designed policy and program interventions.

A number of global issues are also affecting international development cooperation. For example, the consequences of climate change, biodiversity loss, environmental degradation, and disaster risk are already clearly evident in developing countries. The effects are already visible in terms of observable negative consequences, particularly for the most vulnerable populations living in the affected regions. Furthermore, these environmental issues are further exacerbating the existing challenges of poverty, state fragility, and global health.

Partially as a response to the increasing inter-relationships and complexity of these challenges, the United Nations (UN) member states adopted the 2030 Sustainable Development Agenda in 2015 with the aim to end poverty, fight inequality, and tackle climate change by 2030. In order to make progress towards these measurable goals, a comprehensive monitoring system was designed, encompassing 17 universally applicable Sustainable Development Goals (SDGs) accompanied by 169 targets and 230 indicators.

The SDG framework is a significant improvement over the previous Millennium Development Goals (MDGs), particularly in measuring progress towards achievement of the goals. Evaluation, particularly, will play a critical role in the SDGs in ascertaining that the efforts towards solving environmental and development challenges with scarce resources are reaching their objectives. Rigorous evaluation also generates knowledge about successful (and failed) strategies and helps policy-makers and program proponents to hone their approaches so that these are more effective (Uitto et al. 2017). At the same time, the evaluation of complex development interventions is tremendously challenging. Baseline and outcome data are not always readily available, and interventions do not take place in isolation—they are part of a broader system which is subject to change and can be disrupted by natural disasters, conflict, or state fragility. Further, collection of data on environmental and socio-economic indicators can be quite expensive for countries.

To address these limitations and strengthen evaluative evidence, new sources of geospatial data are opening up. They range from rather simple geocoded program data providing location information to overlaying this data with multi-temporal / hyper-spectral remote-sensing imagery and "big data" originating from multiple sensors. Further, the availability of and access to high-performance computational power has made it affordable and efficient to handle complex and large datasets and geospatial data. Cloud-based platforms such as Google Earth Engine, Sentinel Hub, ESRI, Amazon Web Services, GBDX tool box, and others have made the analysis of data possible on a planetary scale. Developments in data science have led to a new class of algorithms based on the principles of machine learning and artificial intelligence that are "data hungry" and work well with high-volume and complex data structures.

While applied geospatial research has embraced the new landscape of data, evaluation practitioners are just beginning to utilize the enormous potential that these data offer for development evaluation. For example, efforts to mitigate global climate change or efforts to reduce deforestation, would benefit from geospatial data and methods from an early stage of identification through monitoring changes.

This article illustrates innovative ways of employing geospatial data in evaluations of environmental interventions. These evaluations were conducted by the Global Environment Facility (GEF) Independent Evaluation Office (IEO) and the German Institute for Development Evaluation (DEval) utilizing geospatial and other "big data" approaches to provide solid evidence on environmental impacts and the drivers associated with them. It shows how geospatial approaches can help address many of the shortcomings in other evaluation methods, such as the availability of baseline data, sampling bias, selection of the right counterfactuals, and addressing results at multiple scales. The paper is structured as follows: Section 2 gives an overview about recent trends and development in the application of geospatial methods in evaluative work. In Section 3, examples of the application of geospatial methods in GEF IEO and DEval projects are presented. Section 4 discusses the potential of geospatial data and methods in the light of their importance to contribute to more policy impacts and Section 5 presents the conclusions.

2 APPLICATION OF GEOSPATIAL METHODS IN EVALUATION

Geospatial methods are increasingly being applied by the evaluation community in some areas alongside other evaluation approaches. The first applications pertained to geographic representation of evaluation data and used traditional geographic information system (GIS) applications (Renger et al. 2002). At the end of the last decade, the application of geographic methods became more common and started to embrace an analytical approach that went beyond mere geographic description (Hites et al. 2013; Azzam and Robinson 2012; Nunn and Newby 2011; Booza et al. 2010).

In the field of development evaluation, the application of geographic data and methods is mainly found in impact evaluations (Palmer-Jones et al. 2012); however, according to Puri et al. (2015), even in this field its "application […] has been relatively unexplored." In recent years and prominently driven by the methodological efforts of AidData and its project partners, the application of geographic data in development evaluation settings has demonstrated a surge in popularity (BenYishay et al. 2017a). Their geospatial impact evaluation methodology was applied by development evaluation practitioners (Isaksson 2017) and demonstrated its benefits in project and program evaluations concerned with environmental protection (BenYishay et al. 2017b; Buntaine et al. 2015). In line with the growth in the application of geospatial data and methods in evaluation is the increasing sophistication and complexity of the applied data and methods. While earlier applications mostly relied on geocoded point data, more recent applications are, for instance, starting to tap into the resources provided by the growing availability of publicly available remote sensing data.

Despite the increasing availability of "big data" derived from internet usage, social media sources, mobile phone data (call detail records), other communication channels, or very high-resolution remote sensing imagery, a large amount of this data has not been tapped into in evaluations. The utilization of these varied data sources mostly remains limited to academic research and, if used in the context of development support, usually takes place within specialized departments of large donor organizations think tanks. Good practice examples of development organizations that leverage the potential of new geospatial data can be found, for instance, with the non-profit Flowminder Foundation[1] that has been advancing the use of mobile phone and satellite data to create small area population and poverty estimates in low- and middle-income countries (Nieves et al, 2017; Patel et al. 2016). Other inter-governmental bodies, such as UN Global Pulse[2] have been utilizing social media, financial transfer data, and phone record data to answer complex development questions. In this regard, it is also important to mention efforts by organizations such as the Food and Agriculture Organization of the UN (FAO), whose powerful "Collect Earth" platform unites the resources of the Google Earth Engine with other publicly available remote sensing data, such as Landsat, MODIS, and Sentinel 2 (Bey et al. 2016). These tools help reduce the initial hurdles to operationalize and use large quantities of data by evaluation practitioners who are not yet experts on working with large volumes of geospatial data and analytical methods.

Beyond methodological challenges, the thematic focus of evaluations also presents its own set of challenges. Environmental issues are rapidly gaining importance in development policy, as the effects of global sea-level rise, rising temperatures, and an increasing number of severe weather events are affecting vulnerable parts of the global population. However, these topics that are specifically related to environment and development are characterized by several problems, such as differing time frames (short project cycles versus long-term environmental changes), scales of interventions (interventions oriented along jurisdictional boundaries), and data fragmentation (Birnbaum and Mickwitz 2009).

Many of these thematic challenges can be addressed with the potential of new forms of geospatial data. Obvious examples consist of visualization techniques using geospatial data. Mapping program outcomes and impacts can greatly enhance the comprehensibility of evaluation results when communicating with policy-makers. More advanced applications consist of geospatial analysis and the integration of geospatial data into statistical modeling. Commonly geocoded program data or contextual variables are derived from geospatial datasets and used, for instance, as covariates in regression modeling or for matching techniques in quasi-experimental approaches. Lastly, more sophisticated are applications related to advanced classification techniques and machine learning approaches in remote sensing data or predictive modeling. Geospatial data and methods also offer large possibilities for continuous program and project monitoring. For instance, remote sensing data allow span analysis beyond the time frame of development project implementation and thus allow an assessment of project or program sustainability.

[1] http://www.flowminder.org/

[2] https://www.unglobalpulse.org/

3 CASE STUDIES APPLYING GEOSPATIAL ANALYSIS IN EVALUATING ENVIRONMENTAL AND DEVELOPMENT INTERVENTIONS

The following case studies present practical examples of evaluative work that were able to utilize the potential offered by geospatial data and analysis to address impacts of biodiversity, land degradation, and disaster risk management interventions.

3.1 Impact evaluation of GEF support to protected areas and protected area systems

Over the last 25 years, the GEF, as the financial mechanism of the Convention on Biological Diversity (CBD), has been providing financial support amounting to more than US$3.4 billion in grants and an additional US$12.0 billion in raised co-financing for the protection of almost 2.8 million km2 of the world's terrestrial ecosystems. A substantial portion of the GEF's support is dedicated to strengthening protected areas and protected area systems and ensuring their sustainability.

The authors at the GEF IEO undertook an impact evaluation of GEF's long-term support to protected areas and protected area systems. The study was challenging due to the varied and complex nature of the projects and programs implemented on multiple spatial and temporal scales (GEF IEO 2016). Other challenges encountered during the evaluation included information gaps on GEF support, limited global time series data, and difficulties in identifying comparator groups, to establish counterfactuals.

To address the data gaps, we collected evidence from a variety of sources including global data sets on remotely sensed forest cover and vegetation productivity data. These data sets were complemented by in-depth case studies, portfolio analysis, and field visits to gather information on causal factors. Geospatial analysis including overlay analysis and forest loss analysis using double difference were then applied.

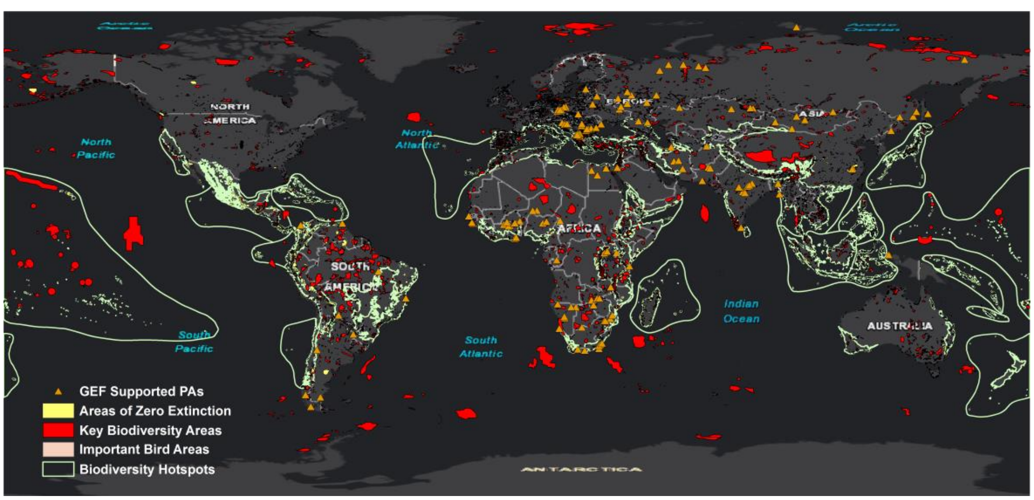

Figure 1. Globally distributed GEF supported protected areas were spatially overlaid with sites of conservation importance. This geospatial analysis shows that the GEF supported protected areas are located in biodiversity hot spots. (Source: GEF IEO 2016)

Geospatial analysis first and foremost provided valuable insights into the relevance of GEF interventions in biodiversity. Figure 1 demonstrates this point wherein the geospatial overlay analysis of GEF supported protected areas with the areas of significant biodiversity presence showed that GEF was investing in globally significant sites with high biological diversity or “hot spots”. The results from the application of geospatial analysis to measure environmental outcomes using remotely sensed satellite data on forest loss demonstrated that, in general, GEF-supported PAs had better conservation outcomes (less forest loss) compared to the buffers, and the PAs that were not supported by the GEF (Figure 2) (GEFIEO 2016)

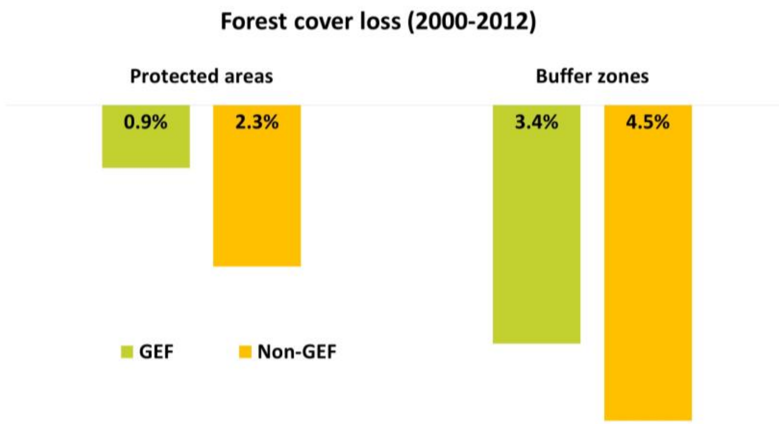

Figure 2. Forest change analysis using satellite data analysis. GEF PAs compared with non-GEF and adjoining buffer zone. (Source: GEF IEO 2016)

3.2 Value-for-money analysis in land degradation projects in the GEF

In environmental and other development interventions, a key question often relates to whether projects deliver value for money. This issue is even more important today with competing challenges placed on scarce resources. The authors at the IEO applied geospatial approaches to assess whether GEF interventions in land degradation projects delivered value for money (GEF IEO 2017).

First, GEF project locations were geocoded. Next, data from the Global Land Cover Facility was used to measure outcomes in terms of vegetation productivity, forest fragmentation, carbon stocks and sequestration, and land cover change. These two data sets were then integrated with a set of other geographically varying variables including nighttime lights, population, distances to roads and rivers. A series of quasi-observational experiments were employed including propensity score matching and machine learning techniques. Causal tree analysis was applied to account for (a) potential variation in treatment effects across different socio-political and environmental conditions, and (b) uncertainty in underlying assumptions and data. The analysis provided the estimates of carbon sequestered as a result of the GEF intervention. These were converted into monetary terms using the principles of natural capital accounting (Costanza et al. 2014).

Overall, the analysis showed that GEF support, globally, has been effective in improving environmental conditions and provides positive returns on investments in terms of carbon sequestered (Figure 3).

The machine learning regression tree model using the gridded biophysical and socio-economic data variables as independent variables further highlighted the role of factors such as the time after project closure, access to electricity, and the "initial state of the environment" in influencing environmental outcomes of GEF interventions (GEF IEO 2017). In general, project impacts were observed to be larger after a period of approximately five years past project closure, and in areas with poorer initial environmental conditions. Higher impacts were also observed to be closely associated with electricity access.

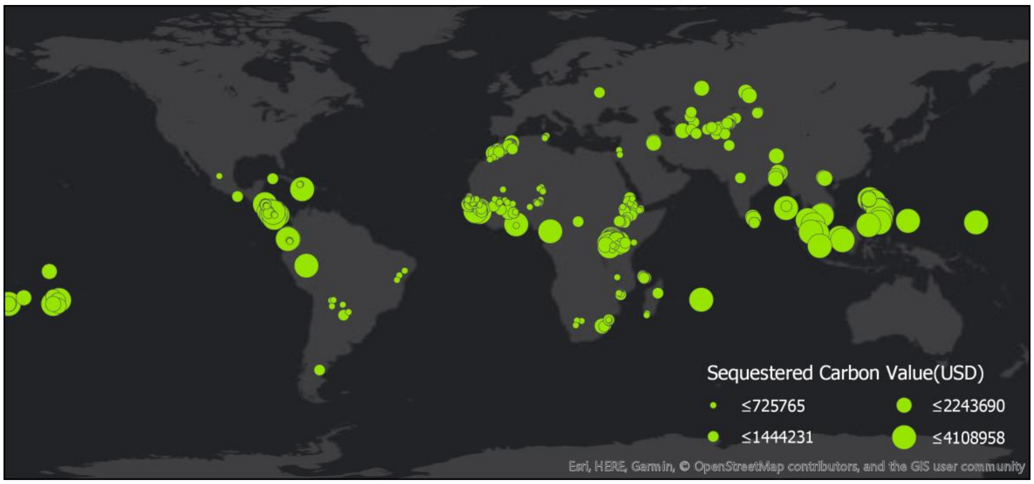

Figure 3. Economic valuation of carbon sequestrated (USD) at each GEF supported project site. The study showed positive carbon sequestration outcomes in most projects. (Source: GEF IEO 2017).

3.3 Evaluating land-use planning and disaster risk management in the Philippines

DEval, the German Institute for Development evaluation, is an independent evaluation institute that aims to provide the German government, German implementation agencies, and local development partners with knowledge about the impacts, efficiency, and sustainability of strategic programs and projects of German development policy. The mandate of DEval covers all of Germany's official development assistance (ODA) to partner countries and institutions. In the process of conducting a rigorous project evaluation of a complex technical development program concerned with a comprehensive and participative land-use planning approach in the Philippines (Garcia Schustereder et al. 2016), DEval devoted a substantial part of its work to assess the outcomes and impacts of the intervention toward the goals surrounding disaster risk management and disaster preparedness among local municipalities.

The Philippines is located in an exposed area of South East Asia which is frequently affected by large tropical cyclones and storm surges, as well as other natural disasters such as volcanic activities and tsunamis, and terrestrial hazards such as landslides. In the light of these challenging environmental conditions, the German Gesellschaft für International Zusammenarbeit (GIZ) implemented a technical development intervention to improve land-use planning, natural resource management, and disaster risk management. Within the so-called "Environment and Rural

Development" (EnRD) program, several component projects were devoted to technical measures in disaster risk management, such as the development of GIS-based disaster risk management planning, the installation of early warning systems for floods, and training and awareness-building measures for the population.

The team applied a statistical quasi-experimental research design (based on propensity score matching[3]) of treatment and control municipalities to be able to attribute impacts of the intervention on the programs' efforts. In the concluding phase of the project, DEval started the implementation of rigorous impact evaluation to assess the outcomes and impacts of the intervention (c.f. Leppert et al. 2018).

The evaluative task was complicated by the large tropical storm Haiyan, which devastated the intervention region in November 2013, just between the baseline and end-line data collection. As official statistical estimates of the effects of the storm proved insufficient for linking the programs' efforts to the observed impacts, the team utilized geocoded meteorological data on wind speed and direction to develop a model of storm intensity based on the weather model of Global Forecasting Systems (GFS). Based on this model, a statistical estimation of wind speed and storm surge intensity was developed and the results were applied to the statistical model to control for the confounding effect. Geographic data on different spatial levels played a key role in answering the evaluation questions. For instance, the team used remote sensing data on forest cover to assess the environmental situation in local municipalities and villages. This external validation of self-reported survey data helped, for instance, to assess the degree of deforestation in the intervention and control municipalities.

Furthermore, the geocoded household data obtained through data collection in the region, combined with digital terrain data (Aster GDEM) and land cover data, allowed for a relatively precise assessment of the potential affectedness and exposure of households to natural hazards such as flooding and landslides (30 m ground resolution) (Figure 4).

The impact evaluation showed that the intervention was able to improve the capacities of municipal planning personnel related to the consideration of disaster risk management activities in technical activities and planning. However, analysis at the household level showed that the expected positive outcomes were significantly lower. While the goal of improving administrative capacity for disaster risk management was fulfilled, the potentially affected households did not substantially benefit from better information by public officials and did not significantly improve their individual disaster preparedness.

[3] In cases where a randomized control trial is ethically or technically not possible, propensity score matching is an econometric procedure that uses statistical characteristics (before the intervention starts) that influence the intervention and that are correlated to the outcome of the intervention. It creates "statistical twins" that will allow for an identification and statistical attribution of the intervention effects.

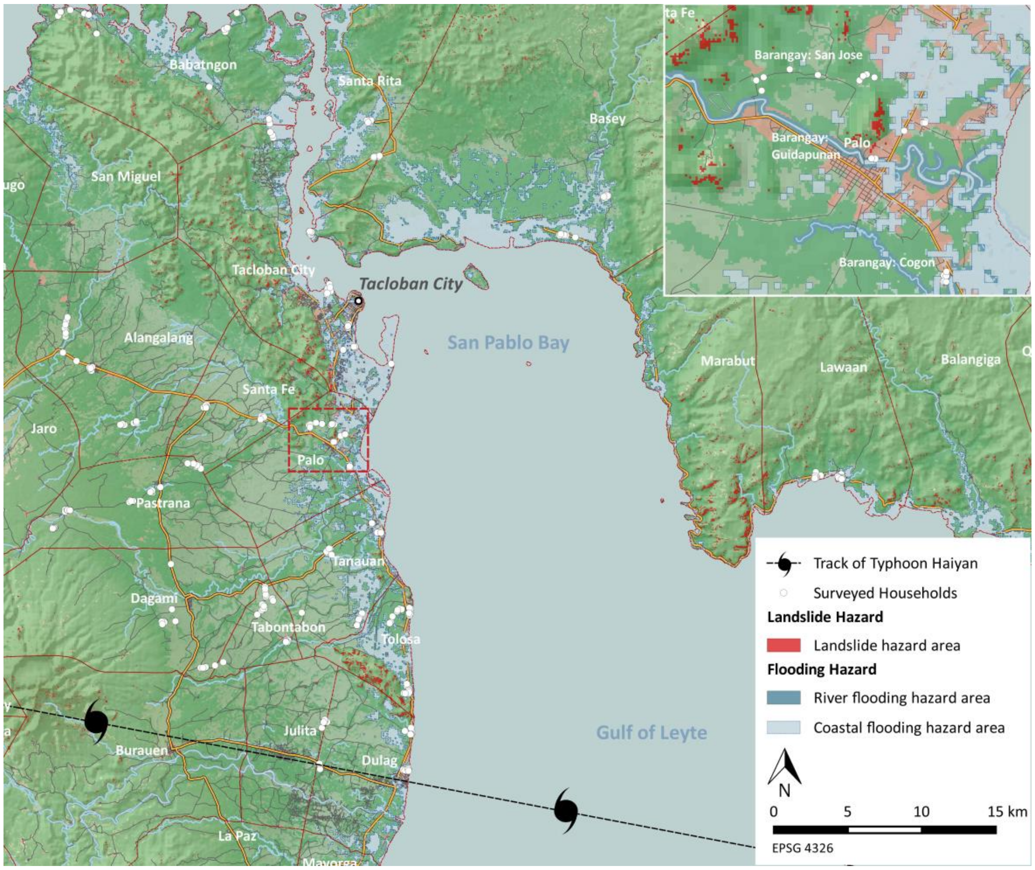

Figure 4. Example of the simplified hazard assessment in the Tacloban area, Philippines (Source: Authors' own draft).

In addition, a geo-statistical approach (geographically weighted regression) was selected to assess the degree of "spillover" of the intervention outputs into non-treated control sites. Different neighborhood-weighting matrices (w-matrices) were developed in order to assess the degree of connectivity between municipalities in the evaluation region and helped to assess the extent to which information about land-use planning and materials provided in the intervention were transmitted to neighboring "untreated" municipalities. Beyond mere contingency matrices of distances and inverted distances, the team decided to use a weighting matrix based on travel time derived from the Google Maps API. This approach was chosen as the geographic heterogeneity in the region is large and travel times will be able to express the actual (rather than the theoretical) degree of connectedness between municipalities. The results of the geographically weighted regression show that the effects of the intervention did significantly influence neighboring municipalities. The quality of land-use plans was thus not only improved in the treatment but partially also in the control municipalities.

However, as focusing solely on survey data will reveal relatively little about changes materializing in the human environment, DEval is currently cooperating with remote sensing experts from the Faculty of Geo-information Science and Earth Observation Earth System Analysis Unit at the University of Twente (ITC).

Figure 5. Remote Sensing analysis of the municipality of Tanauan (Leyte, Philippines) before and after Typhoon Haiyan to assess disaster damage and recovery using Geoeye and WordView VHR satellite imagery. In January 2014 large parts of the municipality are uninhabitable. Machine learning algorithms can be used to train for the detection of structural features such as temporary shelters (lower left corner). (Source: Authors' own draft)

In order to measure visible changes in disaster recovery and disaster risk management, the team uses very high-resolution remote sensing imagery (up to 50cm ground resolution) derived from commercial vendors (Pleiades, WorldView, GeoEye), open source data (MODIS, Landsat, DMSP-OLS), and drone data (exemplified in Figure 5). Coupled with a machine learning-based classification algorithm for land cover change and proxy-based socio-economic recovery in the post-disaster setting of the greater Tacloban area of the Philippines, the analysis will provide insights into the extent and speed of recovery of municipalities after Typhoon Haiyan. It is supposed to improve the understanding of post-disaster recovery in urban and rural areas.

The results will be analyzed based on a system of socio-economic indicators and will be triangulated using survey data from the abovementioned impact evaluation. This combination would allow for a detailed comparison of disaster risk management activities in intervention and control sites, as well as of the individual households covered in the survey. The results of the geospatially supported impact evaluation as well as the remote sensing research project will support development practitioners and local partners in their efforts to develop better and more effective measures of disaster risk management techniques and to assess the degree of sustainability of program efforts.

The following table summarizes the use and contributions of geospatial methodologies in the evaluations described above:

Table 1. Objectives, geospatial methods, and data in the presented case studies

Study / Evaluation	Objective	Geospatial Methods	Geospatial Data	Contribution
Protected Area (PA) Impact	To assess the impact of GEF support to PAs and PA systems	Spatial overlay, BACI, double difference, propensity score matching	Satellite data-derived forest cover, GIS layers of project locations, GIS layers of biodiversity hotspots	Assess impact at global level when the baseline was not available
Value-for-money analysis in land degradation projects of the GEF	To assess the value for money of GEF's support to land degradation interventions	Propensity score matching, causal tree, value transfer approach	Satellite data-derived forest cover loss and vegetation productivity; GIS data on socio-economic and physical attributes	Assess impact, quantify the value for money, identify factors associated with outcomes
Comprehensive land-use planning and disaster risk management in the Philippines	To assess the outcomes and impact of 10-years of land-use planning intervention and to quantify and evaluate the outcomes of disaster recovery and disaster risk management	Propensity score matching, accessibility analysis, hazard mapping, diffusion analysis (geographically weighted regression), support vector machine-(SVM) and convolutional neural network (CNN)-based-based land-use and land cover classification	Geocoded survey data, remote sensing data on tree cover, GFS meteorological data, very high-resolution satellite imagery (Pleiades, WorldView 2/3, GeoEye), MODIS land cover, DMSP-OLS NTL	Assess program impact at municipal level, improve statistical matching, compare perceived and "objective" disaster risk exposure, assess the success of disaster recovery and disaster risk management, measure small- to medium-extent land cover and land-use change

4 HOW DOES NEW DATA FOR GEOSPATIAL ANALYSIS CONTRIBUTE TO EVALUATIONS?

As the previous examples have demonstrated, geospatial analysis is increasingly being used to examine program effects and sustainability in evaluation, which can then improve program design. It effectively complements traditional evaluation methods by adding the inherent spatial component to the analytical design, providing deeper insights about the conditions and factors that influence the outcomes and impacts of development interventions. This information on the outcomes and the drivers is valuable for policy-makers in providing an objective evidence base for designing programs for better impact.

In addition to measuring, monitoring, and evaluating the results of an intervention, geospatial analysis helps in identifying areas that are the most relevant and that should be prioritized for future interventions in program design. Another major advantage is that these methods are transparent, replicable, and dynamic, and have the ability to generate real-time feedback. They also play a useful role in disseminating results through both static and interactive dynamic maps and visualization, which are easy to understand and help decision-makers to comprehend complex environmental and social phenomena.

In order to increase the adoption and application of geospatial tools and analysis, evaluation units need to work in multidisciplinary teams, and enter into collaborative arrangements with universities and research institutions. For example, in the evaluation of the protected areas conducted by the GEF IEO, the core evaluation team was multidisciplinary in composition, with skills in quantitative, qualitative, and spatial analyses, and specializations in the natural and social sciences. Different analyses were performed in collaboration with the Global Land Cover Facility at the University of Maryland, NASA, the IUCN World Commission on Protected Areas–Species Survival Commission Joint Task Force on Biodiversity and Protected Areas, and the Institute of Development Studies. In the case of DEval's Philippine land use planning evaluation, the core team consisted of political scientists, economists, and geographers. In the remote sensing component, technical expertise is being contributed by geo-informatics and remote sensing experts from the Dutch ITC. Finding a common language between disciplines can be challenging but it has proven feasible in the projects presented. A key advantage of these multi-disciplinary teams is the potential to tap into a wide set of methods and data as well as being able to combine these in new and innovative ways. As mixed-method and multi-method approaches are continuously gaining popularity in evaluative work, so is the work conducted by more heterogeneous project teams. This trend is complemented by the move towards multidisciplinary research in the geospatial research community.

Lastly, new and innovative ways of communication need to be found and established to channel the often complex findings into policy decisions Interactive formats involving maps, data visualization, and shorter written products might be a good alternative to improve policy through quick feedback on the relevance and likely impact of decisions.

5 CONCLUSIONS

This article presented applications of geospatial analysis to address the relevance and impacts of environmental interventions in evaluation. Geospatial data have the potential to answer new and increasingly complex evaluative topics and questions that are of interest today. By bridging data-related constraints that are common to traditional evaluation approaches, such as missing baseline information, insufficient data, or confined thematic scope, geospatial data and analysis helps overcome some of the existing limitations that are encountered in evaluations on a regular basis. Other opportunities for applying geospatial data and analysis include adaption, the effects of global climate change, global poverty, international migration, sustainable rural and urban development. In all these areas, geospatial methods could be effectively combined with other quantitative and qualitative evaluation approaches to address a number of complex issues.

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