A Proof-of-Concept of Integrating Machine Learning, Remote Sensing, and Survey Data in Evaluations: The Measurement of Disaster Resilience in the Philippines

Lech, Malte; Ghaffarian, Saman; Kerle, Norman; Leppert, Gerald; Nawrotzki, Raphael; Moull, Kevin; Harten, Sven

1/2020

DEval Discussion Paper

A PROOF-OF-CONCEPT OF INTEGRATING MACHINE LEARNING, REMOTE SENSING, AND SURVEY DATA IN EVALUATIONS

The measurement of disaster resilience in the Philippines

2020

Malte Lech

Saman Ghaffarian

Norman Kerle

Gerald Leppert

Raphael Nawrotzki

Kevin Moull

Sven Harten

ITC UNIVERSITY OF TWENTE.

DEval GERMAN INSTITUTE FOR DEVELOPMENT EVALUATION

Abstract

Disaster resilience is a topic of increasing importance for policy makers in the context of climate change. However, measuring disaster resilience remains a challenge as it requires information on both the physical environment and socio-economic dimensions. In this study we developed and tested a method to use remote sensing (RS) data to construct proxy indicators of socio-economic change. We employed machine-learning algorithms to generate land-cover and land-use classifications from very high-resolution satellite imagery to appraise disaster damage and recovery processes in the Philippines following the devastation of typhoon Haiyan in November 2013. We constructed RS-based proxy indicators for N=20 barangays (villages) in the region surrounding Tacloban City in the central east of the Philippines. We then combined the RS-based proxy indicators with detailed socio-economic information collected during a rigorous-impact evaluation by DEval in 2016. Results from a statistical analysis demonstrated that fastest post-disaster recovery occurred in urban barangays that received sufficient government support (subsidies), and which had no prior disaster experience. In general, socio-demographic factors had stronger effects on the early recovery phase (0–2 years) compared to the late recovery phase (2–3 years). German development support was related to recovery performance only to some extent. Rather than providing an in-depth statistical analysis, this study is intended as a proof-of-concept. We have been able to demonstrate that high-resolution RS data and machine-learning techniques can be used within a mixed-methods design as an effective tool to evaluate disaster impacts and recovery processes. While RS data have distinct limitations (e.g., cost, labour intensity), they offer unique opportunities to objectively measure physical, and by extension socio-economic, changes over large areas and long time-scales.

Keywords: remote sensing, disaster risk management, socio-economic change, machine learning, climate change

Zusammenfassung

Zunehmende Wetterextreme und Naturkatastrophen sind Folgen des Klimawandels. Aufgrund dieser steigenden Risiken rückt die Resilienz der Bevölkerung im Katastrophenfall als zentrales Thema in den Vordergrund und hat zunehmende Bedeutung für politische Entscheidungstragende. Dennoch bleibt die Messung des mehrdimensionalen Konzepts der Katastrophenresilienz eine Herausforderung, da sie Informationen sowohl über die physische Umgebung als auch sozioökonomische Faktoren erfordert. In dieser Studie wird eine Methode entwickelt, um aus Fernerkundungsdaten (RS-Daten) Indikatoren zu entwickeln, die Aspekte des sozioökonomischen Wandels approximieren und somit messbar machen (Proxy-Indikatoren).

Zu diesem Zweck wurden Algorithmen des maschinellen Lernens eingesetzt. Mit Hilfe dieser Algorithmen wurden aus hochauflösenden Satellitenbildern Klassifizierungen für Landstruktur und Landnutzung konstruiert, um Katastrophenschäden und Wiederaufbauprozesse auf den Philippinen nach der Zerstörung durch den Taifun Haiyan im November 2013 zu messen. Aus den RS-Daten wurden die Indikatoren für N=20 Barangays (Dörfer) in der Region um die Stadt Tacloban im zentralen Osten der Philippinen berechnet. Diese auf RS-Daten basierenden Indikatoren wurden mit detaillierten sozioökonomischen Informationen kombiniert, die für eine DEval-Evaluierung im Jahr 2016 erhoben wurden. Die Ergebnisse der statistischen Analyse zeigen, dass der schnellste Wiederaufbau nach der Katastrophe in städtischen Barangays zu beobachten war, die ausreichend staatliche Unterstützung (Subventionen) erhielten und über keine Katastrophenerfahrung verfügten. Im Vergleich hatten soziodemografische Faktoren allgemein stärkere Auswirkungen auf die frühe (0-2 Jahre) als auf die spätere (2-3 Jahre) Wiederaufbauphase. Es konnte nur ein bedingter Bezug zwischen der deutschen Entwicklungszusammenarbeit und den Wiederaufbauerfolgen festgestellt werden.

Diese Studie versteht sich als Nachweis der Machbarkeit, weniger als detaillierte statistische Analyse. Sie belegt, dass hochauflösende RS-Daten und Techniken des maschinellen Lernens innerhalb eines integrierten Methodendesigns als effektives Werkzeug zur Bewertung von Katastrophenauswirkungen und Wiederherstellungsprozessen eingesetzt werden können. Trotz spezifischer Einschränkungen (hohe Kosten, Arbeitsintensität etc.) bieten RS-Daten einzigartige Möglichkeiten sowohl Umweltbedingungen als auch sozioökonomische Veränderungen über große Gebiete und lange Zeiträume hinweg objektiv messen zu können.

Keywords: Fernerkundung, Katastrophenrisikomanagement, Sozioökonomischer Wandel, Maschinelles Lernen, Klimawandel

Imprint

Authors

Dr Malte Lech[1]
Saman Ghaffarian[2]
Prof Dr Norman Kerle[3]
Dr Gerald Leppert[4]
Raphael Nawrotzki[5]
Kevin Moull[6]
Dr Sven Harten[7]

Responsible

Dr Sven Harten

Design

MedienMélange:Kommunikation!, Hamburg
www.medienmelange.de

Editing

Jannet King

Bibliographical reference

Lech, M., S. Ghaffarian, N. Kerle, G. Leppert, R. Nawrotzki, K. Moull, S. Harten (2020): A Proof-of-Concept of Integrating Machine Learning, Remote Sensing, and Survey Data in Evaluations. The Measurement of Disaster Resilience in the Philippines. DEval Discussion Paper 1/2020, German Institute for Development Evaluation (DEval), Bonn.

ISBN 978-3-96126-114-7 (PDF)

Published by

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

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

The German Institute for Development Evaluation (DEval) is mandated by the German Federal Ministry for Economic Cooperation and Development (BMZ) to independently analyse and assess German development interventions.

DEval Discussion Papers present the results of the ongoing scientific study of evaluation and the effectiveness of development cooperation, thus contributing to relevant expert debates on evaluation, social science methods and development cooperation. The discussion papers are geared towards academics and practitioners in the field of evaluation, methodology research and development cooperation.

DEval Discussion Papers are written by DEval evaluators and external guest authors. In contrast to our evaluation reports, they do not contain any direct recommendations for German and international development organizations.

Although DEval Discussion Papers are internally peer-reviewed, the views expressed in them are only those of the authors and – unlike our evaluation reports – do not necessarily reflect those of DEval.

All DEval Discussion Papers can be downloaded as a PDF file from the DEval website:
http://www.deval.org/en/discussion-papers.html

[1] Dr Malte Lech, Former Evaluator at the German Institute for Development Evaluation (DEval). Contact: malte.lech@gmail.com.

[2] Saman Ghaffarian, University of Twente. Contact: s.ghaffarian@utwente.nl.

[3] Prof Dr Norman Kerle, University of Twente. Contact: n.kerle@utwente.nl.

[4] Dr Gerald Leppert, Senior Evaluator – Team Leader at the German Institute for Development Evaluation (DEval). Contact: gerald.leppert@DEval.org.

[5] Dr Raphael Nawrotzki, Evaluator at the German Institute for Development Evaluation (DEval). Contact: raphael.nawrotzki@DEval.org.

[6] Kevin Moull, Evaluator at the German Institute for Development Evaluation (DEval). Contact: kevin.moull@DEval.org.

[7] Dr Sven Harten, Deputy Director at the German Institute for Development Evaluation (DEval). Contact: sven.harten@DEval.org.

CONTENTS

Figures

Tables

ABBREVIATIONS AND ACRONYMS

BMZ	German Federal Ministry for Economic Cooperation and Development
CLUP	Comprehensive Land-Use Plan
CNN	Convolutional neural networks
DEval	German Institute for Development Evaluation
DILG	Department for the Interior and Local Governance
DMSP	Defense Meteorological Satellite Program
DRM	Disaster risk management
EnRD	Environment and Rural Development (Programme)
GBM	Gradient-boosting method
GEE	Google Earth Engine
GIS	Geographic Information System
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH
IRA	Internal Revenue Allotment
ITC	University of Twente's Faculty for Geo-Information Science and Earth Observation
LBP	Local binary patterns
LCLU	Land cover and land use
NRG	Natural resource governance
PHP	Philippine Pesos
RS	Remote sensing
SVM	Support vector machines
UAV	Unmanned aerial vehicle
VHR	Very high resolution
VIIRS	Visible infrared imaging radiometer suite

1. INTRODUCTION

International development cooperation is increasingly concerned with addressing climate change and assisting vulnerable populations in adapting to its adverse impacts. Evaluating adaptation to climate change is unique because changes in the natural environment (climate change) and the socio-economic situation (adaptation) both need to be measured.

This leads to numerous challenges. First, climate change manifests itself as a heterogeneous group of environmental impacts. These range from an increase in sudden-onset natural disasters such as tropical storms to more gradual changes such as desertification and sea-level rise. These environmental changes can impact large geographical areas and develop over long time periods. Second, human responses to climate change are highly diverse, including changes in agricultural production techniques (e.g., drought-resistant seeds, irrigation systems), infrastructure, and built environment (e.g., storm shelters, dams, sea-walls), or mobility patterns (e.g., climate-related human mobility). Assisting populations in adapting to these challenges requires a diverse set of programmes and strategies.

Surveys and censuses have been used by evaluators to measure social and economic changes. However, such methods of data collection are both labour and cost intensive and not very flexible in terms of their scope and application. For example, it is often not possible to collect relevant baseline data prior to a natural disaster, making it difficult to evaluate disaster recovery. Similarly, it would require multiple rounds of survey data collection to capture gradual climatic changes and related impacts that develop over decades. However, recent technological developments in remote sensing (RS) methods and data availability may facilitate the evaluation of climate-change adaptation and post-disaster recovery processes.

RS is a technology used to detect, collect, and monitor the earth's surface by measuring its reflection and emission of radiation. This is done by a collection platform that is remote from the target being observed, such as a satellite, aeroplane, or unmanned aerial vehicle (UAV). RS sensor systems are able to collect information ranging from visible to invisible (e.g. radar and infrared) features that can be traced using their specific spectral signature. As such, RS data are ideal to measure changes in the physical environment, including climate change. Moreover, some changes in the physical environment may be used as proxy indicators or indirect measures of socio-economic changes. For example, RS data can be used to measure the extent of slums as an indicator of poverty in a given region. However, the most comprehensive approach would be a mixed-methods evaluation design that combines RS data with survey data to provide a complete picture of the impacts of climate change as well as adaptation and recovery processes. As such, this study[8] has two main objectives:

1. develop a (semi) automated approach to generate RS-based proxies for socio-economic change, which can be used to assess post-disaster recovery;
2. combine these RS-based proxies with survey data to contextualize the recovery processes.

These objectives highlight the exploratory nature of this study. Specifically, it can be seen as a "proof of concept" of using machine-learning-based RS data analysis to measure environmental as well as socio-economic changes and of combining RS with survey data for a more comprehensive analysis of recovery processes.

We first develop a conceptual framework for the generation and use of RS-based proxies of socio-economic change. Second, this framework is applied to the case of post-disaster recovery in the Philippines following the devastation of typhoon Haiyan.[9] The discussion paper is divided into five sections. Section 2 provides a

[8] This study was designed as a joint project by the University of Twente's Faculty for Geo-Information Science and Earth Observation (ITC) Earth Systems Analysis Unit and the German Institute for Development Evaluation (DEval).

[9] Typhoon Haiyan, which is the subject of this study, devastated large parts of the central Philippine archipelago on 7–9 November 2013.

context for the use of RS data to measure socio-economic change and climate change. Section 3 highlights the proxy-based approach to measure socio-economic change. Section 4 presents the case study of disaster risk management (DRM) in the Philippines. Section 5 discusses the important findings and concludes the paper. Based on his study, a recent publication (Kerle et al., 2019) highlights the benefits and limitations of using remote sensing to support evaluation work.

2. USING REMOTE SENSING DATA TO MEASURE SOCIO-ECONOMIC CHANGE AND CLIMATE CHANGE

One of the most pressing questions of our time is whether humanity can find effective answers to climate change. Current state-of-the-art prognoses anticipate a likelihood that certain extreme weather events will increase in magnitude and frequency (Davies et al., 2009; Field and IPCC, 2012). In addition to these irregularly occurring natural shocks, overarching long-term climate-change phenomena exist. Examples of these so-called stressors are desertification, an increasing global temperature, and rising sea-levels. Both shocks and stressors induce social stress and may cause lasting damage to the human environment (Turner et al., 2003).

Adaptation processes play a central role in the search for solutions to climate change. The term ”adaptation” refers to the process of adjusting to climate change and its effects in order to moderate or avert the harm to human systems caused by stressors and shocks (Edenhofer, 2014). However, human response to stressors is different from the human response to shocks. While stressors require adaptation of human and natural systems, typically through increased adaptive capacities or established enabling environments (i.e. system-level changes in the environmental, socio-economic, and/or institutional system), shocks require a similar, but different response strategy.

While a proper response to shocks also benefits from an increase in adaptive capacities and economic capabilities, it requires, in addition, systematic disaster risk management (DRM) to increase the preparedness for likely disasters. If proper proactive DRM is absent in the event of a disaster, ad hoc reactive risk management (i.e. risk coping) is required, which is typically less effective (Matthews, 2012; Leppert, 2015). The performance of post-disaster recovery depends on all response measures: the level of adaptive capacities and economic capabilities, and, in particular, established proactive DRM.

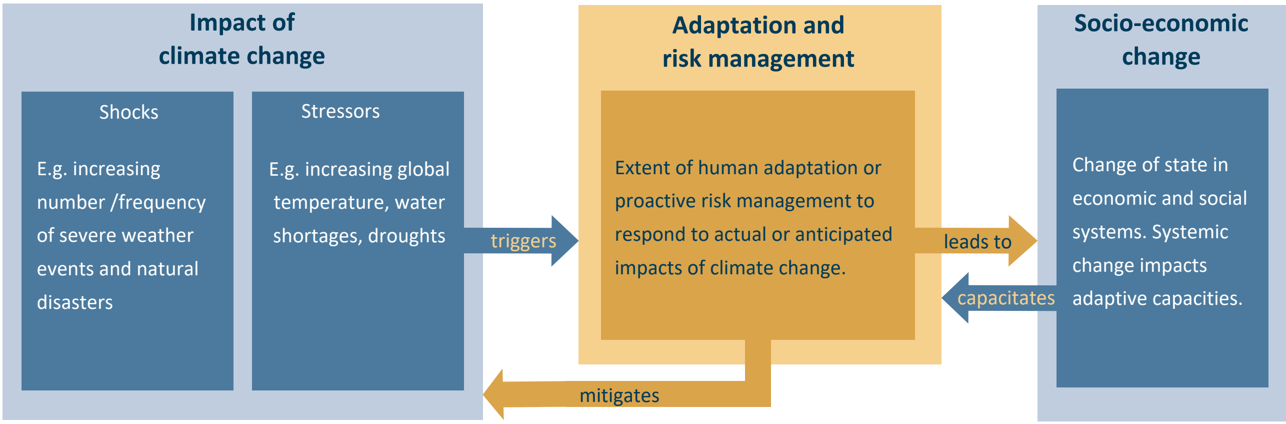
Interdependencies between experienced shocks and vulnerability also impact disaster-related losses and damages, as well as recovery performance. Bunched or repeated shocks can result in increased vulnerability for future crises (Matthews, 2012; Leppert, 2015). A high degree of exposure to shocks and stressors may reduce communities’ future adaptive capacities (Shackleton et al., 2014; Villanueva, 2010). By contrast, resilient communities show a high capacity for adaptation and are able to maintain or retain their essential functions even in the case of extreme weather events (Edenhofer, 2014).

The adaptation process underlies a dynamic logic of social progress (Toye, 2017) and is therefore directly or indirectly connected to a range of social and economic factors (Villanueva, 2010). As Figure 1 illustrates, climate-related shocks and stressors may trigger adaptation and risk-management activities and may ultimately lead to socio-economic change. In this sense, socio-economic change refers to “the way the state of a system changes over time (…)” due to adaptation (Newell et al., 2005). The scale and dynamics of socio-economic changes are highly variable, from the seemingly static traditional rural communities to the dynamic, growing megacities that are in perpetual development and change.

In response to shocks and stressors, climate-change adaptation and risk management can trigger socio-economic change. With reference to the previous example of a typhoon, affected communities might implement early-warning systems and evacuation plans, the construction of sea-walls and, ultimately, relocation from hazard zones – activities that increase their resilience with respect to future shocks and stressors. However, as mentioned above, experienced shocks may also reduce the future adaptive capacity of communities. If a typhoon were to completely destroy the infrastructure of a community, a social system might struggle to adapt in a timely manner. As a consequence of the lack of adaptation, people’s livelihoods deteriorate.

Furthermore, vulnerability to climate change arises from certain socio-economic conditions, such as the economic capability of households or the existing infrastructure (Shackleton et al., 2014). While a typhoon may completely destroy the harvest of a rural farmer, resulting in debt and poverty, an urban resident whose shop is destroyed may find employment in a local factory. These examples of typhoon recovery show the complex relationship of shocks and stressors on one side and socio-economic change on the other side. Their relationship is mediated by the extent of human adaptation and (proactive) risk management, which in itself depends on current adaptive capacities and economic capabilities.

Figure 1 Impact of climate change and socio-economic change



Source: own figure.

For these reasons, measuring changes in socio-economic conditions is highly important for politicians, urban planners, and policy makers alike. Frequently, censuses or population surveys are employed to measure changes in socio-economic conditions (Lech et al., 2018). Yet, these forms of data collection are expensive and usually conducted only every five or 10 years. This static data collection lacks the temporal resolution to measure dynamic socio-economic changes, particularly if these changes are caused by sudden-onset climate events such as tropical storms. An emerging alternative to measuring and tracking socio-economic changes is the use of remote-sensing (RS) geospatial data.

RS data are collected via some type of sensor (similar to a camera) attached to a satellite, aeroplane or drone (Kerle, 2015). RS techniques can be used to measure most structural features of the outer layer of the earth, including elevation and topography, vegetation cover, and infrastructure, to mention just a few. This makes RS ideally suited to map the land cover over large areas. Moreover, satellites orbit the earth on regular and short temporal intervals, which allows for an effective monitoring of changes in surface features (e.g., changes in building structures or vegetation coverage). Satellites have been orbiting the earth for decades now, and the archived RS data allows a detailed study of changes over long periods of time.

Advances in technology over the past 15 years have made RS data increasingly promising as an effective tool to measure disaster impacts and recovery. For example, the spatial resolution has increased from 10–15 m per pixel (ASTER, SPOT satellites) to c. 0.5 m (e.g., WorldView, GeoEye satellites), which can provide detail necessary to assess structural damage and land-cover changes. In addition, the revisit time (minimum time between two observations) has declined from several weeks to a few days, meaning that data are now often available within hours after an event.

In DRM, optical images are the primary source of information as they allow detailed information on structural changes and damages. Usually these RS images are captured during daylight hours but, recently, night-time images have emerged as a useful source of information. The Defense Meteorological Satellite Program (DMSP) generates night-time images that provide insightful time series of mainly anthropogenic light emissions (mainly corresponding to exterior illumination such as street lamps). Drastic declines in local light emission have been linked to disaster damage (Li et al., 2018), while the subsequent increase in light may be used as a proxy for recovery (Andersson et al., 2015; Ghaffarian et al., 2018).

As an alternative to optical images, thermal sensors can be used to measure irregular sea-surface temperature increases, which have been linked to stronger tropical storms. Similar, ambient temperatures can be used to monitor the threat of heatwaves and wildfires. In addition to optical and thermal images, electromagnetic radiation can be used to measure detailed topographic features. As an example, in the Philippines, researchers used detailed topographic information to recalculate the storm-surge hazard following a major tropical storm (Lagmay and Kerle, 2015).

The fact that RS primarily captures the physical environment can be seen as a severe limitation when the socio-economic situation or changes therein are of interest. However, many socio-economic parameters can be readily linked to physical proxies that are in turn observable in RS data. For example, the number of buildings correlates with population number, while actual location, size, building/roof materials, state of repair (as far as visible), building density etc. can be linked to the socio-economic condition of their inhabitants (Sliuzas and Kuffer, 2008). Likewise, progress has been made to approximate crops grown, the method of planting and care, and crop yield from RS data (Bolton and Friedl, 2013; Mulla, 2013) and to link it to the socio-economic reality on the ground; automated monitoring systems exist for some of these.

For example, in response to adverse climate change, RS data may be used to measure crop destruction and productivity losses in flooded areas, or the declining number of livestock as a result of prolonged drought. Moreover, recent studies have used RS data to identify and characterize slums and similarly deprived areas (Kohli et al., 2012, 2013; Gevaert et al., 2017). Being able to locate such sub-standard dwellings in turn can be linked to both physical and social vulnerability (e.g. Ebert et al., 2009).

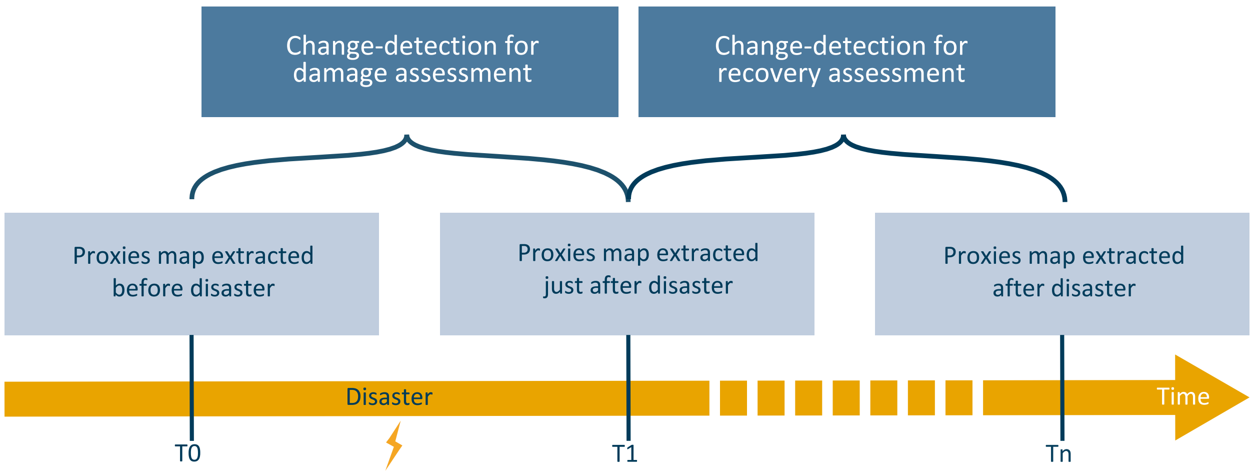
However, correctly classifying RS data to capture socio-economic conditions and changes is methodologically challenging. One promising approach that we explore in this study is the use of machine-learning algorithms. These algorithms allow a computer to “learn” how to recognize certain patterns from a large set of examples, including patterns not even known to the researcher. For example, to capture evidence of disaster damage, we may provide the computer with a large number of damage examples. This enables the machine-learning algorithm to understand the desired damage class in its varying forms and allows it to accurately classify disaster damage across diverse geographic locations and settings (Duarte et al., 2018; Vetrivel et al., 2018).

3. THE PROXY-BASED APPROACH TO MEASURE SOCIO-ECONOMIC CHANGE

As briefly outlined in Section 2, changes in physical attributes may be used as proxies to evaluate socio-economic changes. As such, this study employs “proxies”, or indirect measurements, following initial studies to assess vulnerability (Flax et al., 2002; Morrow, 1999), resilience (Burton, 2012), damage (Bevington et al., 2010; Bradshaw, 2004), and recovery (Rubin et al., 1985).

Figure 2 provides a flow chart to depict the proxy-based approach to measuring post-disaster recovery. Two main steps can be distinguished. The first step constitutes the damage assessment. In this step, evaluators extract RS data shortly before (T0) and directly after (T1) the disaster took place. This allows the detection of damage caused by the disaster. In the second step, evaluators then extract RS data directly after the disaster took place (T1) as well as after a longer period of time (Tn), which then allows the detection of the degree of post-disaster recovery. The subscript “n” indicates that recovery may be measured at multiple time points, such as two (T2) or three years (T3), depending on the type of infrastructure observed, as reconstruction may take varying amounts of time.

Figure 2 The conceptual framework for post-disaster recovery assessment using remote sensing-based proxies



Source: own figure.

The conceptual framework of the proxy-based approach was developed generically to be applicable across study sites, disaster types, and geo-spatial contexts (Kerle et al., 2019). Changes in different physical features are associated with different changes in the socio-economic conditions of the local population. Table 1 provides a selection of proxies as well as a brief description of what is measured, and the socio-economic dimension that is approximated.

Table 1 Examples of proxy indicators computed from RS data

Proxy	Proxy Name	Description of measurement	Approximation of socio-economic dimension
1	Buildings	The area covered by buildings. Changes in this measure permit an estimation of the damage inflicted and the scale of reconstruction needed	Economic loss and recovery
2	Proportion of built-up area	Area covered by buildings expressed as proportion of total area	Measure of the level of urbanization
3	Impervious surface	Changes in this measure permit a computation of the amount of debris covering the surface	Debris as obstacle for economic business operations
4	Large-scale industry	Measurement of buildings associated with large scale-industry	Indicator of industrial capacity and local labour market
5	Vehicles	The number of vehicles	Economic activity
6	Boats	The number of boats	Level of economic activity in fisheries sector
7	Arable land	Measurement of the area that can be used for agricultural production	Use of agriculture for livelihood recovery
8	Proportion vegetated area	Area covered by vegetation expressed as a proportion of total area	Measure of access to natural resources

Proxy	Proxy Name	Description of measurement	Approximation of socio-economic dimension
9	Roof material	Measurement of the texture and colour of roofs	Roof material is associated with housing quality and income level of occupants. It may be used as indicator of slum areas and presence of poverty.

Source: own table.

A few examples help to illustrate the proxy-based approach (see also, Kerle et al., 2019). The difference in the area covered by buildings (Proxy 1) before and after a disaster can be used to measure the degree of structural damage in a given community. When the average economic value of buildings in a neighbourhood is known, we can assess the economic losses caused by a natural disaster (Bevington et al., 2010; Chen et al., 2003). Change in the impervious surface area allows us to detect if debris is blocking roads (Proxy 3). We can then use this information to approximate the economic losses due to an obstruction of important transportation networks (Ghaffarian et al., 2018; Kerle and Hoffman, 2013). In terms of recovery processes, the number of boats on lakes/ocean/coastline near a specific barangay (Proxy 6) or the number of vehicles on a given street (Proxy 5) can be used to approximate the degree of economic activity in a region. If a population fully recovers from a disaster, we would anticipate that at least the same number of boats and vehicles are present after a sufficiently long recovery period (Brown et al., 2010; Platt et al., 2016). Similarly, RS data can be used to measure the presence of irregular clusters of a specific roof types (Proxy 9). Such indicators can be used as a proxy to measure the expansion of squatter settlements or slums (de Almeida et al., 2016; Ghaffarian et al., 2018).

4. CASE STUDY OF DISASTER RISK MANAGEMENT IN THE PHILIPPINES

4.1 Study Context

4.1.1 Climate Change in the Philippines

Climate change will lead to an increase in the frequency and severity of extreme weathers events such as tropical cyclones and floods, associated with substantial socio-economic cost and in most cases also loss of life (Combest-Friedman et al., 2012). Recently, Löw (2018) highlighted that total economic losses caused by weather catastrophes in 2017 totalled approximately USD 330 billion. According to the MunichRE study, the Asia-Pacific region accounted for approximately 44% of all natural disasters, but more than 65% of all fatalities (Löw, 2018).

Given these figures, it is not surprising that the Philippines is especially affected by the burdens of natural disasters and severe weather events (Jha et al., 2018). For decades, the Philippines has been among the top five countries in terms of annual number of natural disasters. Its geographic location makes it highly exposed to severe weather events such as tropical cyclones but also geophysical hazards. Since 1990, more than 565 natural disasters have affected the Philippines and caused more than 70,000 casualties. Among these are approximately 20 typhoons, which strike the Philippine archipelago on an annual basis (GFDRR, 2017). While not every occurrence of a typhoon is a catastrophic event, and not all Philippine regions are exposed to the same degree to the potential adverse effects, the numbers underline the burden caused by such events. According to figures by Jha et al. (2018) based on the EM-DAT database for the Philippines, between 2000 and 2016 natural disasters claimed more than 23,000 lives and injured over 173,000 persons; average annual damage came to approximately USD 1.2 billion.

4.1.2 Disaster Risk Management in the Philippines

It is thus not surprising that DRM plays an important role in the Philippine public administration. As a reaction to these challenging conditions, national policies for disaster risk mitigation were formulated (Government of the Philippines, 2010) and have consequently been mainstreamed into guidelines for urban and land-use planning (Jha et al., 2018; MSU-Iligan Institute of Technology et al., 2015). Furthermore, the process of implementing functional DRM was supported by a multitude of international donor organizations, which contributed to capacity development for DRM in addition to local stakeholders, provided equipment and machinery, and engaged in larger technical measurements to reduce disaster risk, specifically for coastal hazards. While this was applied throughout the Philippines, the Eastern Visayas Region has been a focal area for these support measures.

The relatively strong focus on improving capacities in the field of DRM in the Visayas area is therefore not surprising. Tacloban City and its adjacent municipalities are frequently affected by tropical cyclones passing through the Philippine archipelago. One of the most severe events occurred on 7–9 November 2013, when typhoon Haiyan made landfall in Eastern Samar, before passing through San Pablo Bay and Leyte. Official estimates approximate the number of casualties at 6,300, with a further 1,000 people missing (Del Rosario, 2013). Following the destruction caused by the typhoon, the region received the lion's share of post-disaster reconstruction support (both nationally and internationally). However, even before typhoon Haiyan triggered a substantial development effort in DRM, the Philippines, and specifically the socio-economically disadvantaged Visayas region, were recipients of international and German donor-support schemes.

The German Gesellschaft für Internationale Zusammenarbeit (GIZ) and its predecessor organizations have been the main German development organizations involved in capacity development of Philippine municipalities and provincial planning authorities in the field of land-use planning, natural resource management as well as DRM. Since 2005, the technical components of the German contribution to DRM in the Philippines were implemented through the Environment and Rural Development (EnRD) programme of Philippine–German cooperation. It was mandated by the German Federal Ministry for Economic Cooperation and Development (BMZ), and implemented from 2005 to 2015. The aim of the programme was to foster sustainable rural development in the Philippine Visayas Region by means of support in policy fields such as Environmental Protection, Food and Nutrition, DRM, and improved municipal land-use planning (GIZ, 2014). The programme was later complemented by a post-Haiyan reconstruction support component to provide immediate support to tackle the effects of typhoon Haiyan in November 2013.

While the Natural Resource Governance (NRG) component of the EnRD programme aimed at integrating DRM-sensitive planning into provincial and municipal land-use planning, the DRM component included more immediate measures, such as the implementation of flood early warning systems and mitigation measures such as reforestation and slope stabilization (Table 2). Land-use planning can significantly enhance the mitigation of disaster risks, by imposing regulations on settlement in disaster prone areas, and by enforcing building standards, making constructions able to withstand the effects of natural disasters (Becker et al., 2010). At the same time, planning-related measures usually take time to materialize and do not show immediate results (Leppert et al., 2018).

Table 2 An overview of the relevant goals of the EnRD programme for DRM measures

Disaster Risk Management (DRM)	Natural Resource Governance (NRG)	Support for reconstruction in Haiyan-affected areas
Establishment of Flood Early Warning Systems, including precipitation pattern data	Development and approval of Provincial Development and Physical Framework Plans	Development and revision of disaster and conflict preventive reconstruction plans
Establishment of Risk Mitigation measures such as Slope Stabilization and Reforestation	Development approval of Comprehensive Land-Use Plans (CLUP)	Implementation of reconstruction plans in cooperation with governmental, civil and non-government agencies and stakeholders. Reconstruction efforts include, for example, shelter, streets, schools, health and evacuation centres, waste management, energy and water supply, and the revitalization of the economy
Increased stakeholders' awareness for DRM	Development and approval of 5-year Barangay Development and Annual Investment Plans	
Capacitated LGU include DRM in munici-pal land-use and development planning	Establishment of Capacity Development Networks	

Source: GIZ (2014).

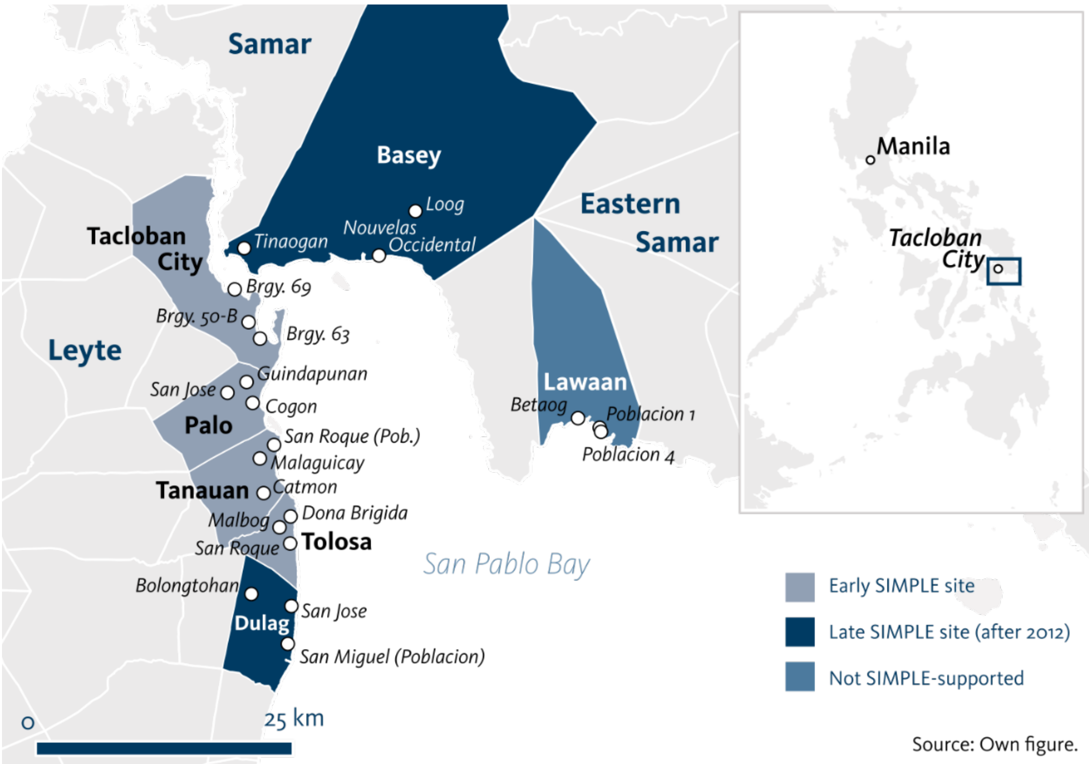
4.1.3 Study Region

Three barangays[10] in each of seven municipalities in the greater Tacloban area were selected. These barangays were covered in DEval's impact evaluation of enhanced land-use planning.

The survey of the impact evaluation covered a large area (the whole province of Leyte as well as neighbouring provinces). In the study region, many municipalities were affected by typhoon Haiyan to some extent. However, we limit this study to seven municipalities due to the following reasons. First, we needed to ensure that for the geographic area very high-resolution images were available. Second, RS data come at a cost, and budget constraints required us to narrow the selection. Despite these limitations, the case-study region and the selected barangays offer a unique combination in terms of their affectedness by typhoon Haiyan in 2013 and their status as recipients of German development support (Figure 3). We used a combination of multi-temporal RS imagery, ranging from before typhoon Haiyan to the phase immediately after the event, as well as imagery of the reconstruction phase in the following years. More details on the RS imagery is provided in section 4.2.1.1.

[10] A barangay is the Philippine equivalent of a village or a part of a city/municipality. It represents the smallest official administrative units in the administrative hierarchy. The barangay captain is the official head of the village, elected for a period of three-years, and responsible for all administrative duties in the village.

Figure 3 Seven municipalities selected for the case study



Source: Own figure.

4.1.4 Objectives

The objective of the case study is to demonstrate the process involved in analysing high-resolution RS imagery to measure socio-economic changes such as disaster resilience. We explore the potential for using automated methods (e.g., machine learning), and for integrating RS analysis into existing evaluation approaches.

4.2 Data and Methods

4.2.1 Data

Remote Sensing Data

The imagery used in this case study was collected by commercial satellites, in particular WorldView 2 and 3 (Satellite Imaging Corporation, 2018a), Geoeye-2 (Lockheed Martin Space Systems, 2018), and Pleiades (Satellite Imaging Corporation, 2018b). We purchased the data from European Space Imaging Corps for four time points (March 2013, November 2013, April 2016, March 2017) for seven municipalities at a cost of about USD 10 per km². The multi-spectral images are very high resolution, with a pixel size ranging from 0.5 m (panchromatic images) to 2.0 m (multispectral images). See Annex A for detailed source information regarding the purchased images.

Survey Data

To demonstrate the application of RS data in evaluations, we linked the geospatial information with survey data collected during the DEval impact evaluation on enhanced land-use planning in the Philippines (Leppert et al., 2018). For the evaluation, extensive panel survey data at the household, barangay, and municipal levels were collected. In 2012, the baseline survey covered a total of 37 GIZ intervention municipalities and 63 comparable control municipalities (N=100).[11] Control municipalities were selected from all available municipalities in the two study regions using a propensity-score matching technique (Garcia Schustereder et al., 2016). Within each municipality, three barangays were randomly selected. Either the barangay captain or, in their absence, a senior member of the barangay council was interviewed, resulting in a total of N=300 barangay-level interviews. In each of the barangays, 10 households were randomly selected (N=3,000). The same municipalities, barangays, and households were revisited in 2016 for endline data collection. Attrition at household level was negligible at 5%, with no attrition at the other levels (e.g., barangay, municipality). For more detail on the survey data see Leppert et al. (2018). In the following analysis, we will mostly refer to the data collected at the barangay (village) level, while other analyses refer to municipal-level data.

With regard to the RS data analysis, we were only able to process RS data for N=20 selected barangays due to budget constraints and the complicated processing structure. This number was further reduced to a minimum of N=13 barangays for some analyses due to cloud coverage and cloud shadow rendering the computation of some RS-based proxies infeasible. We purposely selected barangays that had been badly affected by typhoon Haiyan. While we tried to include both intervention (SIMPLE-treated municipalities) and control municipalities in the selection for the case study, because of the way the GIZ intervention had rolled out, with many intervention municipalities located near Tacloban City, SIMPLE-supported barangays are over-represented in our case study.

The survey data at the barangay-level contain extensive information on planning, DRM and previous exposure to disasters. Several items provided information on the barangays' affectedness by typhoon Haiyan. The barangay dataset was completed by socio-economic and demographic information derived from the Department for the Interior and Local Governance (DILG), including structural characteristics of barangays in 2012, such as the municipal income class and other socio-demographic information.

4.2.2 Data Processing and Variable Construction

Remote Sensing Data Processing and Development

For the measurement of disaster effects and recovery processes with very high-resolution RS imagery, we needed to classify a very large number of pixels. In order to detect disaster-related patterns in land cover and land use (e.g., debris, structural damage to buildings), we employed machine-learning algorithms. Specifically, we used a certain type of Gradient Boosting Method (GBM). GBM is a supervised classification technique that belongs to regression and classification tree models (Friedman, 2001). The GBM-based methods are widely used for RS data analysis, such as scene classification (Chan and Paelinckx, 2008; Zhang et al., 2016). However, the traditional GBMs need to be tuned for several parameters and are more likely to suffer from overfitting than other machine-learning algorithms such as Support Vector Machines (SVM). In 2008, (Chen and Guestrin, 2016) developed the Extreme Gradient Boosting (XGBoost) method, which can be considered a regularized version of GBM that overcomes most of its limitations. The superiority of the XGBoost-based approaches for LCLU classification of very high-resolution RS images was shown in recent studies (Georganos et al., 2018; Ren et al., 2017). Given these advantages, we used the XGBoost method to compute proxy maps from very high-resolution satellite images in this study (Kerle et al., 2019).

The computation of the RS-based proxies of social and economic change was a four-step procedure, as outlined graphically in Figure 4. The four distinct steps are: pre-processing, land-cover and land-use classification, post-processing, and extraction of proxies (Kerle et al., 2019).

1. *Pre-processing*: Satellite images obtained at different time points may have different inclination angles of the sensor as well as inaccuracies in geo-referencing, leading to the coordinates not necessarily matching perfectly. We therefore had to rectify and register the images to allow for a correct comparison between LCLU maps obtained at different points in time. In addition, we merged satellite image tiles

[11] Between 2012 and 2016, eight of the 63 control municipalities started receiving the intervention and therefore "switched" to the intervention group. The size of the intervention group at endline was therefore 44, the size of the control group was 56.

(mosaicking) to completely cover the particular region of interest (ROI). Finally, we employed shapefiles for ROIs to clip the rectangular raster images to the barangay boundaries, and used those for the image classification described next. All pre-processing steps were conducted using ArcGIS software.

2. LCLU classification: We employed the XGBoost algorithm for the land-cover and land-use classification. In order to recognize patterns for an accurate classification, the XGBoost algorithm requires "training areas". These training areas were selected using Environment for Visualizing Images (ENVI) image analysis software, and used as input for the main classification model, which was developed in a programming environment (Python script).[12] We improved the classification precision by providing the XGBoost algorithm not only with spectral information (e.g., different colour bands) but also with information on the texture of a given land-cover and land-use (LCLU) class. To this end, we employed Local Binary Patterns (LBPs) as an effective textural information extraction method (Kuffer et al., 2016; Mboga et al., 2017). Based on a grey-level co-occurrence matrix, LBP (5 x 5 kernel) computes simple textural information, such as mean, variance, homogeneity, and entropy for each image. To differentiate building types, the roof colours were detected, based on the brightness values of the pixels.

3. Post-processing: Post-processing involved removal of pixels in areas obscured by clouds as well as the modification of mixed classes.

4. Extraction of proxies: We first obtained the number of pixels for each LCLU class for a given barangay. We then computed the coverage area (in m2) for relevant LCLU classes and expressed this number as a percentage of the total barangay area. However, some proxies, such as the presence of vehicles and boats, which could not be extracted from the LCLU maps, were extracted manually using both panchromatic (grayscale) and multispectral (multicolour) images.[13]

Proxies were extracted at various time points: before disaster (T0), just after disaster (T1), and two years (T2) and three years (T3) after the disaster. As discussed in Section 3, computing changes between these time points allows us to assess disaster damage and recovery processes.

Although the developed approach provided overall good accuracies for LCLU classifications, we observed some inaccuracies in the results due to a number of reasons. First, the presence of clouds led to misclassifications. Similarly, the algorithm had difficulties in correctly classifying pixels in areas where cloud shadow influenced the visual appearance of the landscape. Second, different radiometric and spectral values in the merged images for one barangay led to inaccurate classification results for trees, crops, and grass lands.

Survey Data

The survey data used in this study was collected during DEval's impact evaluation on comprehensive land-use planning in the Philippines (Leppert et al., 2018). For the impact evaluation, the survey data was cleaned and processed (for details see Leppert et al., 2018). Table 3 provides summary statistics of the relevant socio-economic and demographic variables that we obtained from Leppert et al. (2018) and employed in this study.

[12] The selection of the training areas was challenging for some classes, particularly for the land-use classes. For examples, distinguishing large-scale industrial buildings from formal buildings without using auxiliary data was difficult. Hence, we used our knowledge of the area and the panchromatic images, in addition to multispectral images, to select the training areas as accurately as possible.

[13] The vehicles and boats were counted manually because there is not yet an efficient and accurate method for automated extraction.

Table 3 Summary statistics of relevant socio-economic and demographic variables

Variable	N	Unit	Mean	SD
Structural characteristics				
Municipal income	20	1 = High, 0 = Low	0.85	0.366
Level of urbanization	20	1 = City, 0 = Rural	0.150	0.366
Subsidies (Internal Revenue Allotment)	20	Philippine Pesos	115,000,000	15,400,000
DRM-related characteristics				
Perceived disaster preparedness	20	Scale: 1 = Low, 10 = High	7.3	2.27
Previous disaster experience	19	1 = Yes, 0 = No	0.737	0.452
Reconstruction support	15	Philippine Pesos	16,100,000	23,300,000
DRM activities	20	Scale: 0 = Low, 10 = High	5.41	3.20
Local governance				
Experienced Barangay Captain	20	1 = Yes, 0 = No	0.550	0.510
Experience of Mayor	20	Years in office	3.4	2.50
Perceived corruption	20	Scale: 0 = Low, 10 = High	4.55	2.781
Donor support				
SIMPLE intervention	20	1 = Yes, 0 = No	0.850	0.366
SIMPLE intervention start	17	1 = Late, 0 = Early	0.471	0.514
Recipient of other donor-support	20	1 = Yes, 0 = No	0.850	0.366

Source: own table.

We made use of a number of variables outlining the structural characteristics of the barangay. First, we classified barangays according to the income classification of their respective municipality as high (≥PHP 25 million) and low (< PHP 24.99 million). We further expressed the level of urbanization by classifying barangays as located in a city or rural area. The urbanization classification was derived from official Philippine statistical classification and allowed a distinction to be made between barangays located in the provincial capital of Tacloban City and adjacent "rural" municipalities. In addition, the variable "subsidies" captured the amount of DILG Internal Revenue Allotment (IRA) subsidies that a particular municipality received.

A second group of variables captured DRM-related characteristics. These variables are derived from the DEval survey in 2012 (and 2016 for the amount of post-Haiyan reconstruction support). We used the self-reported information to try to assess the perceived degree of preparedness of barangays for future disasters. The variables measure, for a given barangay, the perceived disaster preparedness of the captain (Scale: 1=low, 10=high), whether a natural disaster had previously been experienced (1=yes, 0=no), the amount of reconstruction support received (in Philippine Pesos), and an index of technical and planning-related disaster risk management activities (Scale: 0=low, 10=high).

Governance-related variables seek to differentiate barangays based on administrative capacity. These are approximated by work (years in office) and political experience (more than one tenure) of mayors and barangay captains, as well as their self-reported assessment of corruption (Scale: 0=low, 10=high).

Lastly, control variables related to donor-support try to allow for a differentiation between "supported" and "not-supported" municipalities and barangays, based on GIZ's land-use planning and disaster risk management intervention "SIMPLE". We accounted for the time spent on project implementation and potential achievements by classifying barangays according to the start of the intervention as early (pre-2009) and late (between 2009 and 2012). Finally, we captured other donor support received by a barangay from other international agencies (not including GIZ).

4.2.3 Statistical Approach

In order to analyse the relationship between changes in LCLU patterns derived from RS data and socio-economic characteristics, factors related to local governance, DRM, and donor support, we relied on basic statistical tests. Specifically, we employed group-mean T-test statistics and ordinary least squares (OLS) regressions with robust standard errors. Using these tests, we could assess which factors and local conditions were statistically associated with damage caused by typhoon Haiyan, and which factors were associated with disaster resilience and recovery performance.

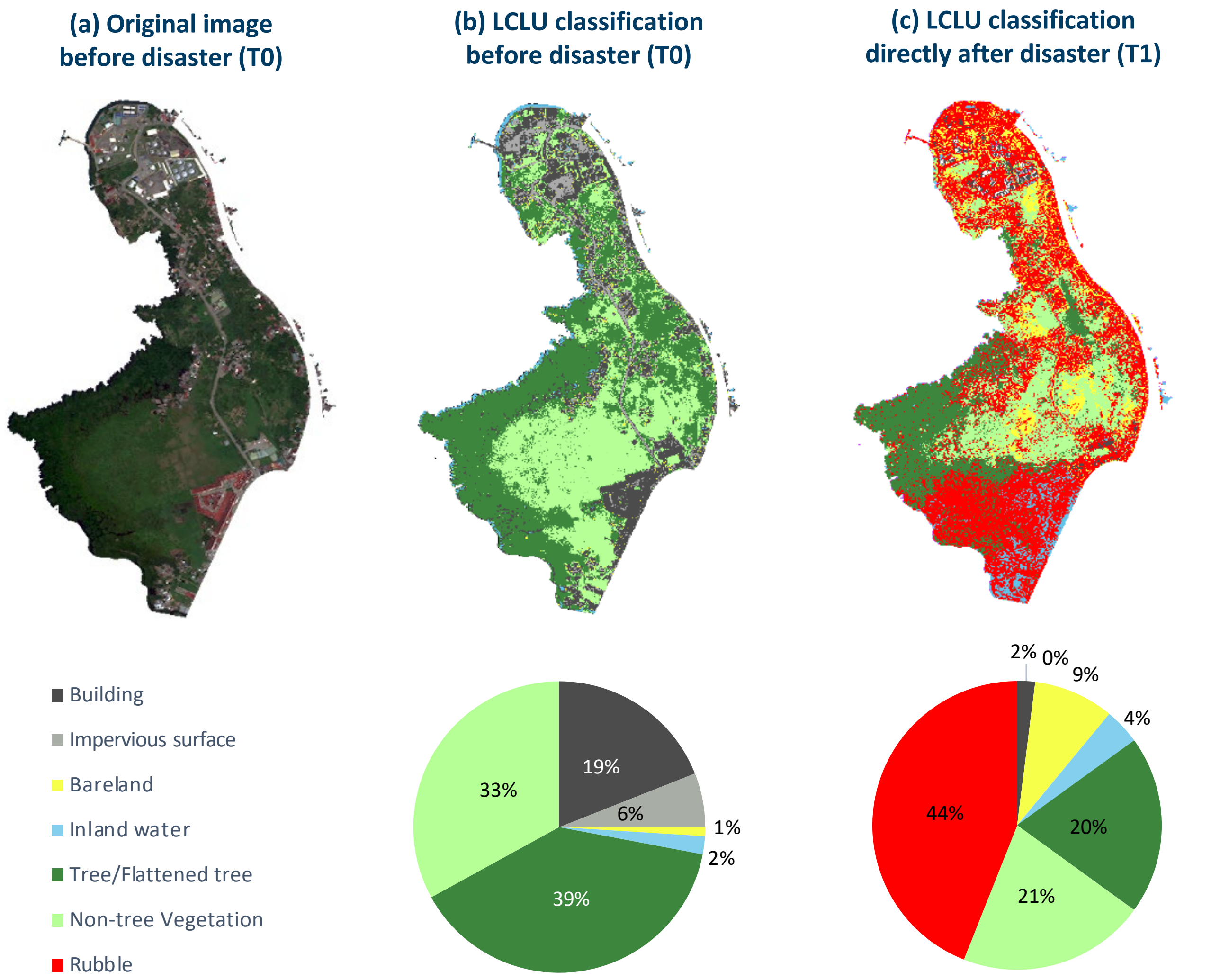
Because all variables derived from the RS analysis (dependent variable) have a continuous level of measurement, the type of socio-economic variable (independent variable) determined the applied statistical test. We used OLS regressions with robust standard errors in cases where both the dependent and independent variables were continuous. Group-mean T-tests were applied in cases where the independent variable was nominal to detect significant statistical differences between the two groups. Due to the small sample size ($N<20$), we considered $p < 0.10$ a significant relationship. The statistical tests were computed using Stata version 13.1.

4.3 Case Study Results and Discussion

4.3.1 Land Use and Land Cover Proxies

Using the XGBoost machine-learning algorithm, we extracted nine RS-based social and economic proxies for four time points: before disaster (T0), just after the disaster (T1), two years after the disaster (T2) and three years after the disaster (T3). Computing changes between the various time points permitted us to assess recovery performance in the statistical analysis. As an illustrative example, we have given the results of the proxy computation for one barangay. We selected barangay 69 (located north of Tacloban City) because it contained most of the relevant LCLU classes. Figure 4 provides a visual depiction of the results of the LCLU classification.

Figure 4 LCLU classification of barangay 69 before and after typhoon Haiyan



Source: own figure.

As can be seen in Figure 4, typhoon Haiyan caused a massive change in the surface of barangay 69. The most striking difference is the change in detectable debris/rubble (colour: red). While no debris was detectable before the disaster (T0), almost 44% of the surface was covered by debris shortly after Haiyan (T1).

Table 4 shows the final extracted proxies (for a description of the proxies and what socio-economic dimension is approximated, see Table 1 in Section 3). The proxies can be used to compute various damage and recovery statistics. For example, difference in the area covered by buildings provides insights into structural damages. After typhoon Haiyan, 91% (1-(36076/3236)*100) of buildings in Barangay 69 were collapsed/damaged (proxy 1). About three years after Haiyan (T3) roughly 74% of the original building stock had been rebuilt ((26852/36076)*100).

Large-scale industry (proxy 4) was hit particularly hard by Haiyan, resulting in widespread damage, leaving only about 8% of the original infrastructure in place (1036/12396). Recovery was much slower than for regular buildings, and three years after Haiyan (T3) only 23% (2840/12396) of the pre-disaster industry had been rebuilt. As such, we can assume that only a fraction of the former workplaces were available to the population, with potentially severe consequences for livelihoods and income-generation opportunities.

Increase in impervious surface area (proxy 3) after the disaster either from the removal of debris on the roads or the reconstruction of new ones, plus an increase in the number of vehicles on the road (proxy 5), indicated a positive recovery of transportation facilities and road network.

An increase in the number of boats (proxy 6) by about 69% ((22/13-1)*100) after three years indicated a positive recovery of livelihood. Similarly, more arable land was available for livelihood pursuits at the end of the recovery period, perhaps as a result of areas formerly used for industry and buildings being repurposed for agricultural production.

Those areas identified as slums (based on a certain type of roof material such as cardboard or metal sheets) near the coast were entirely wiped out by the storm, although other slum neighbourhoods suffered only limited damage (proxy 9). Slum areas re-emerged, but remained about 19% ((1-(3484/4284))*100) smaller in size after three years of recovery (T3). A smaller number of people living in informal settlements can be considered a positive outcome; it most likely results from government interventions or aid provided by international donors or organizations.

Table 4 The extracted results for the selected proxies for Barangay 69, Tacloban

Proxy No.	Proxy Name	Unit	T0	T1	T2	T3
1	Buildings	m^2	36,076	3,236	25,236	26,852
2	Proportion of built-up area	%	26	2	28	29
3	Impervious surface	m^2	12,132	3,236	28,482	28,270
4	Large-scale industry	m^2	12,396	1,036	2,564	2,840
5	Vehicles	count	9	1	15	10
6	Boats	count	13	2	32	22
7	Arable land	m^2	2,422	16,740	13,998	6,106
8	Proportion vegetated area	%	71	41	61	64
9	Roof material	m^2 (slum area)	4,284	0	3,138	3,484

Note: typhoon Haiyan hit the Philippines on 7–9 November 2013; T0 = before disaster (satellite: World View 2), T1 = just after disaster (satellite: Geo Eye 1), T2 = two years after disaster (satellite: Geo Eye 1), T3 = three years after disaster (satellite: World View 2).
Source: own table.

While all nine RS-based proxies were constructed during the analysis, we employ only a selection of three proxies as dependent variables in our statistical analysis. Specifically, we computed changes (T0–T1) in buildings (damaged buildings), impervious surface (debris), and large-scale industry (damaged industrial areas) and expressed these changes in percentage of the total area. “Damaged buildings” as well as “debris” are used to approximate damage to urban areas. The proxy indicator “damaged industrial areas” serves to gain insights into the extent to which the regional economy might be affected. For example, directly after Haiyan made landfall, an average of 54% of all buildings showed substantial damage.

We also computed the difference between the local condition just after the disaster (T1) and two years after the disaster (T2), as well as the difference between the local condition two years after the disaster (T2) and three years after the disaster (T3). These differences allowed us to capture growth rates of building reconstruction (proxy 1) and industry recovery (proxy 4). For example, between the time just after typhoon Haiyan struck and two years later, the building stock had increased by 348%, indicating a sizeable damage recovery. Table 5 provides summary statistics of the employed RS-based proxies.

Table 5 Summary statistics of selected RS-based socio-economic proxies across all study barangays employed in the statistical analysis

Variables	Δ Time	N	Unit	Mean	SD
Damaged Buildings	T0 - T1	13	% total building area	54.1	29.4
Debris	T0 - T1	14	% total building and industrial area	21.4	20.4
Damaged industrial areas	T0 - T1	14	% total industrial area	47.9	28.7
Building reconstruction	T1 - T2	15	% growth rate of building area	347.7	496.3
Building reconstruction	T2 - T3	17	% growth rate of building area	18.0	33.4
Industry recovery	T1 - T2	13	% growth rate of industrial area	397.9	652.9
Industry recovery	T2 - T3	13	% growth rate of industrial area	25.0	38.9

Note: typhoon Haiyan hit the Philippines 7-9 November 2013; T0 = before disaster, T1 = just after disaster, T2 = two year after disaster, T3 = three years after disaster.
Source: own table.

4.3.2 Integration of RS Analysis into Evaluative Work

Damage Assessment

As the first part of our analysis, we investigated the association between disaster damage and socio-economic characteristics. Table 4 shows the relationship between our outcome measures (damaged buildings, debris, and damaged industrial areas) and various socio-economic determinants, including municipal income, previous disaster experience, perceived disaster preparedness, and the level of experience of the barangay captain.

Table 6 Damage by socio-economic status, disaster risk management and local governance

Variable name	Damaged buildings (n=12)			Debris (n=13)			Damaged industrial areas (n=9)		
	beta	Mean (m2)	T (sig.)	beta	Mean (m2)	T (sig.)	beta	Mean (m2)	T (sig.)
Municipal income									
High		63	-2.3 (***)		26	-1.4 (*)			†
Low		25			8				
Level of urbanization									
City		93	-3.9 (***)		50	-3.7 (***)		96	-3.0 (***)
Rural		42			14			55	
Previous disaster experience									
Yes		52	1.0 (n.s.)		22	0.5 (n.s.)		67	-0.0 (n.s.)
No		70			29			67	
Perceived disaster preparedness									
	3.7		1.1 (n.s.)	1.6		0.7 (n.s.)	4.2		1.4 (n.s.)
Experienced captain									
Yes		62	-1.3 (n.s.)		28	-1.4 (n.s.)		77	-1.2 (n.s.)
No		41			14			57	

**p < 0.10; **p < 0.05; ***p < 0.01, n.s. = not significant, † = not calculated due to insufficient data. T0 = before disaster, T1 = just after disaster, T2 = two years after disaster, T3 = three years after disaster.*
Source: own table.

We found a highly significant difference in the extent of typhoon damage by level of urbanization. Generally, urban areas experienced much more destruction than rural areas. We also found some statistically significant relationships by wealth level, with the largest destruction in the wealthiest barangays. These relationships can be largely explained by the storm track. Typhoon Haiyan passed Tacloban City approximately 20 km to the south. The wind speed and rotation of the storm caused a substantial storm surge in the San Pablo bay area and was the main driver for extensive damage observable in the provincial capital. The extent to which buildings and industrial infrastructure was damaged by the storm was not related to the experience and perception of the barangay administrators. As such, the physical force of the storm determined entirely the damage caused, and good governance or prior experience and perception of the barangay leadership could not mitigate these effects.

Recovery Performance by Socio-Economic Status

After an assessment of damage caused by typhoon Haiyan, this sub-section focuses on determinants of recovery performance. We generally differentiated between the early recovery phase (T1–T2) and the later recovery phase (T2-T3). We focused on building reconstruction and industry recovery as outcome variables. We found few significant socio-economic determinants on recovery performance, and these were for the early recovery phase (Table 7). For example, in the early recovery phase (T1–T2) building reconstruction was much stronger in urban areas than in rural areas, while there was no significant difference in the later recovery phase (T2–T3). The important function of Tacloban City (the prime urban area) as an economic and transport hub, and its coordination function in the immediate recovery process, might explain its stronger recovery performance. For example, Tacloban City's airport functioned as the main hub for international relief goods and support.

Table 7 Recovery status by socio-economic status

Variable name	Building reconstruction (n=15)						Industry recovery (n=13)					
	T1 → T2			T2 → T3			T1 → T2			T2 → T3		
	beta	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*
Municipal income												
High		407	-0.9 (n.s.)		19	0.9 (n.s.)		505	-1.1 (n.s.)		28	-0.5 (n.s.)
Low		111			36			40			15	
Level of urbanization												
City		1109	-4.7 (***)		9	0.9 (n.s.)		704	-0.9 (n.s.)		30	-0.2 (n.s.)
Rural		158			26			306			24	
Subsidies[a]												
	2.2		2.6 (**)	-0.054		-2.5 (**)	1.03		1.3 (n.s.)	0.008		0.2 (n.s.)

**p < 0.10; **p < 0.05; ***p < 0.01, n.s. = not significant. T0 = before disaster, T1 = just after disaster, T2 = two years after disaster, T3 = three years after disaster. [a]subsidies variable was scaled to million Pesos.*
Source: own table.

Municipal income had no influence on recovery performance, but the amount of subsidies, IRA, was positively associated with building recovery in the early recovery phase. However, for the later recovery phase (T2–T3) the relationship became negative. While IRA subsidies are usually associated with weaker financial performance, the subsidies are likely to have played an important role in financing immediate reconstruction efforts. Yet, the subsidies were unable to support recovery in later years. Industry recovery was not determined by municipal income, urbanization level, or availability of subsidies.

Recovery Performance by Disaster Risk Management (DRM)

In this section, we focus on a group of variables that reflect disaster risk management (DRM) capacities, including previous disaster experience, perceived disaster preparedness, financial reconstruction support, and DRM-related activities in the barangay (Table 8).

Table 8 Recovery performance by disaster risk management

Variable name	Building reconstruction (n=15)						Industry recovery (n=13)					
	T1 → T2			T2 → T3			T1 → T2			T2 → T3		
	beta	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*
Previous disaster experience												
Yes		222	2.5 (**)		13	1.8 (*)		370	0.7 (n.s.)		12	3.3 (***)
No		910			42			728			87	
Perceived disaster preparedness												
	17.0		0.5 (n.s.)	-2.7		-0.8 (n.s.)	-93.4		-1.2 (n.s.)	6.9		1.3 (n.s.)
Reconstruction support[a]												
	-0.3		-0.23 (n.s.)	-1.0		-5.7 (***)	-1.1		-0.5 (n.s.)	-0.3		-0.4 (n.s.)
DRM activities												
	-19.0		-0.7 (n.s.)	0.5		0.2 (n.s.)	-73.4		-1.3 (n.s.)	-6.3		-1.6 (n.s.)

**p < 0.10; **p < 0.05; ***p < 0.01, n.s. = not significant. T0 = before disaster, T1 = just after disaster, T2 = two years after disaster, T3 = three years after disaster. [a]subsidies variable was scaled to million Pesos.*
Source: own table.

Previous disaster experience was significantly associated with both building reconstruction and industry recovery. Barangays with previous disaster experience generally showed lower recovery rates.

Financial reconstruction support led to significantly slower building reconstruction in the later recover phase (T2–T3). This finding may be explained by building policies. It is possible that government reconstruction support was coupled with policies that required storm-proof, high-quality construction material and building types. Compared to light-build housing construction in other regions without reconstruction support, high-quality buildings took more time, resulting in the negative association.

Neither perceived disaster preparedness nor DRM activities in the barangay influenced the rate of building reconstruction or industry recovery.

Recovery Performance by Local Governance

Quality and performance of local government officials can make a large difference in the recovery performance of municipalities in a post-disaster situation. Good governance supports the implementation of planning according to guidelines and safety standards, and improves reliability of public governance. Furthermore, well-implemented and enforced DRM-planning requires coherent and reliable leadership as well as political commitment to the public good.

Table 9 Recovery performance by local governance

Variable name	Building reconstruction (n=15)						Industry recovery (n=13)					
	T1 → T2			T2 → T3			T1 → T2			T2 → T3		
	beta	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*
Experienced barangay captain												
Yes		317	0.3 (n.s.)		18	0.6 (n.s.)		195	1.2 (n.s.)		32	0.7 (n.s.)
No		394			27			634			17	
Perceived corruption												
	-8.2		-2.5 (**)	0.6		2.9 (**)	-7.1		-1.5 (n.s.)	0.2		1.3 (n.s.)
Experience of Mayor												
	-87.3		-2.1 (*)	-3.4		-1.1 (n.s.)	-125.8		-2.0 (*)	-0.6		-0.1 (n.s.)

**p < 0.10; ** p < 0.05; ***p < 0.01, n.s. = not significant. T0 = before disaster, T1 = just after disaster, T2 = two years after disaster, T3 = three years after disaster.*
Source: own table.

However, this beneficial effect of good governance is only partially reflected in our data (Table 9). For example, an increase in the experience of the local mayor (years in office) led to slower building reconstruction and slower industry recovery. Similarly, during the early years, recovery was strongest in those barangays with less perceived corruption. This highlights the importance of trust and accountability of government officials in the early recovery years. Yet, in the later years of adaptation, the sign of the relationship switched, and barangays perceived as more corrupt demonstrated higher building reconstruction rates. Generally, the Philippines is still characterized by relatively high rates of corruption among local governments. At the same time, local governments possess substantial regulatory autonomy with regards to the Local Government Code (Yilmaz and Venugopal, 2013).

Recovery Performance by Donor Support

International donor support played an important role in technical-planning capacity development in the Tacloban area. This included also a focus on planning for natural-disaster events. We investigate the influence of donor support separately for the SIMPLE intervention and support by other (not GIZ) donor interventions (Table 10).

Table 10 Recovery performance by donor support

Variable name	Building reconstruction (n=15)						Industry recovery (n=13)					
	T1 → T2			T2 → T3			T1 → T2			T2 → T3		
	beta	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*	*beta*	*Mean growth rate (%)*	*T (sig.)*
SIMPLE intervention												
Yes		337	0.2 (n.s.)		16	2.2 (**)			†			†
No		416			61							
SIMPLE intervention start												
Late		524	-1.5 (*)		16	0.0 (n.s.)		787	-2.2 (**)		7	1.3 (n.s.)
Early		120			17			50			27	
Recipient of other donor-support												
Yes		85	1.3 (n.s.)		28	-0.3 (n.s.)		870	-1.5 (*)		-16	2.5 (**)
No		443			21			256			37	

**p < 0.10; ** p < 0.05; ***p < 0.01, n.s. = not significant, † = not calculated due to missing data. T0 = before disaster, T1 = just after disaster, T2 = two years after disaster, T3 = three years after disaster.*
Source: own table.

We found slower building reconstruction rates among barangays that received the German-supported SIMPLE intervention. While the general trend is similar for both time periods, the effect was statistically significant only for the later recovery period (T2–T3). Among those that implemented the SIMPLE intervention, barangays that adopted the programme later showed stronger building and industry recovery rates. The evolving nature of the programme and the increasingly climate-risk-aware political context may have led to higher quality and better outcomes in the later phase of implementation.

The existence of other donor support proved effective for industry recovery but only for the early recovery phase (T1–T2). However, in later recovery years we observed signs of a switch in the relationship, with those barangays that did not receive other donor support showing higher recovery rates.

5. DISCUSSION AND CONCLUSION

5.1 Summary of Case Study Results

In this discussion paper we have demonstrated the integration of RS data and related machine-learning-based analysis with survey data for complex evaluations. Using this method, we were able to evaluate damage and the effectiveness of recovery processes following typhoon Haiyan, which made landfall on the Philippines in 2013. Our analysis revealed strongest damage in the urban barangays of Tacloban City and areas with large shares of disadvantaged populations (usually the coastal barangays).

Our analysis of recovery performance showed that the barangays that recovered fastest where those that had no prior disaster experience and were provided with sufficient government support (subsidies). We found that the GIZ-supported SIMPLE programme was related to recovery performance only to some extent. We generally observed strong recovery during the first two years, but substantially slower recovery effects for later years. In addition, we found a stronger recovery performance for industrial areas than for buildings. This tendency may be explained by the strong focus of the government and international organizations on economic capacity and performance.

5.2 Outlook: Strengths and Limitations of the Approach

Combining remote sensing and machine learning with survey data offers many advantages but also has some limitations. These have important implications for future research (see also, Kerle et al., 2019). In general, we see the most promising applications of RS technologies and data within mixed-methods and multi-method evaluation designs. Rather than a stand-alone tool, RS is best seen as a promising addition to the evaluators' toolbox that allows viewing problems from a different angle and thereby broadens the evidence base of evaluations. With this preamble in mind, we now discuss advantages and disadvantages of the use of RS in evaluations:

Advantages: As a first advantage, machine-learning-based analysis of RS data permits the measurement of physical changes over comparably large areas and across multiple time points. Natural disasters are hard to predict, and if the goal is to evaluate disaster-recovery processes and programmes, it is almost impossible to collect baseline survey data before the disaster event. In such a case, RS data offers a convenient way to obtain relevant pre-disaster information on local conditions. Moreover, satellites now orbit the earth with increasing frequency, and their wide coverage makes it possible to measure change processes more precisely and across larger areas. Given the wide coverage of most RS data products, cross-regional, or even cross-country evaluations are possible. This case study has shown that RS data can be used to construct proxy indicators of social and economic conditions and to use these proxies for machine-learning-based classification. This is of particular relevance to the evaluation community, as politicians and policy makers are frequently concerned with the socio-economic conditions of the population in relatively large areas. Moreover, as we have shown in this article, it is possible to join RS data with data from surveys and qualitative interviews. Such a fusion allows the contextualization of the RS data and an exploration of the underlying mechanism of change, and also helps to gain more human-centred insights into patterns of change.

Limitations and future prospects: Our study also revealed a number of disadvantages of RS data. First, the very high-resolution data we employed are very expensive. RS data costs about 10 USD per km^2 for a single time-period, resulting in substantial costs for large areas. Usually, it is not possible for implementing agencies to spend a sizeable amount of their limited budget on the purchase of RS data. Even in our analysis we were only able to purchase RS data for a small selection of barangays for which we had survey data available. This limited the sample size of our analysis and prevented us from using advanced statistical methods. However, it was the goal of this study to demonstrate the use of RS data in evaluations rather than to make comprehensive use of all survey data available.

It is important to mention that many geo-data sources are freely available. For example, the European Space Agency makes multi-spectral RS data from the Sentinel 2 satellite available free of charge. While its resolution is much coarser (10 m) than the data used in this study (0.5 m), it still provides a useful source to measure changes in physical environment. Many other RS data products are freely available and often have specific applications. This includes night-time lights (Li et al., 2018), vegetation indices, topographic information, and land cover and land use (LCLU) classifications of the US Geographical Survey (USGS). New data providers are also entering the market. For example, Planet Labs recently launched a constellation of some 200 small CubeSat satellites that provide approximately daily imagery free for non-commercial use at a spatial resolution of 3 m.

A second limitation of the use of RS data by the average evaluator is the steep learning curve involved in working with the specialized software and format of RS data. Future research should develop user-friendly statistical tools, enabling evaluators and practitioners to easily generate the relevant proxy indicators employed in this study.

A third limitation is the substantial time commitment required for pre- and post-processing of the RS data. Currently, this work requires a GIS expert for geo-rectification of the images, merging of image tiles (mosaicking), detection and removal of parts of images that are contaminated by clouds or cloud shadows. Similarly, it is necessary in a post-processing step to manually check that the LCLU classifications are assigned correctly. Given the complexity of these tasks and geospatial analysis in general, an evaluation team wishing to integrate RS data would have to employ a GIS expert, which could substantially increase staff costs. Future work should aim at automating pre- and post-processing steps, since automation for large areas can become economical, especially when compared with expensive field-based studies. In the meantime, the collaboration with GIS experts at universities or research institutions may be an alternative. While such collaboration comes with their own potential challenges (alignment of research interests and evaluation objectives, different priorities and time schedules, time required for supervision), costs may be lower compared to employing a GIS expert.

A fourth limitation is the problem of distinguishing and classifying structural rubble (which represents evidence of building damage) from debris (which includes flotsam and other washed-up material that can be quickly cleaned up). The potential for misclassification remains, and if damage is overestimated, the rate of recovery is also overestimated, since recovery is defined as the change vector from the post-disaster damage state.

Finally, RS data are one type of so-called "Big Data" resources. It is often not possible to work on regular desktop computers with this type of data. Rather, multi-core servers or super-computers with large amounts of RAM are necessary, particularly when computing intense machine-learning algorithms (e.g. Convolutional Neural Networks) to assign LCLU classifications and to generate the relevant proxy indicators. Rather than purchasing costly hardware, an emerging alternative is computing platforms such as Google Earth Engine (GEE) (Gorelick et al., 2017). GEE, for example, is based on cloud computing, meaning that the analysis procedures are programmed in the web interface, and the processing is done in the cloud, eliminating the need to download vast amounts of data. Moreover, because the actual image data are not made available for download, fewer copyright restrictions apply. GEE is designed to be used by non-experts in RS data analysis and may become a viable resource for evaluators. However, without additional costs, GEE provides only medium-resolution datasets that are primarily suitable for analyses on the national, regional, and global-level scale.

Outlook: The above discussion has shown that integrating RS data has distinct strengths and weaknesses. Yet, satellite technology, cloud computing, and processing speed and power are improving every year, and most of the above limitations will likely be overcome within the next decade. It is therefore the right time for evaluation units and institutes to explore uses and applications of RS data. RS data will be a valuable resource to measure programme impacts that leave a mark on the surface of the earth. Yet, similar or more important, machine-learning-based analysis of RS data can be used to approximate social and economic change. Enhanced machine-learning algorithms and standardized packages, as well as sets of validated proxies for socio-economic change, will increase automation and thus allow for the classification of larger land areas. This discussion paper was intended to provide a real-world example of machine-learning-based analysis of RS data in evaluation and, thus, to sensitize the evaluation community to the potentials and uses of RS data. The future will be technological and driven by "Big Data" and we hope that this paper helps to encourage the use of RS data and technologies in evaluations.

6. REFERENCES

de Almeida, L. Q. et al. (2016), "Disaster Risk Indicators in Brazil: A Proposal Based on the World Risk Index", *International Journal of Disaster Risk Reduction*, Vol. 17, pp. 251–272.

Andersson, M. et al. (2015), "Assessing Recovery from the 2004 Indian Ocean Tsunami: An Application of Night-Time Light Data and Vegetation Index: Recovery from the Indian Ocean Tsunami", *Geographical Research*, Vol. 53, No. 4, pp. 436–450.

Becker, J. S. et al. (2010), "A Synthesis of Challenges and Opportunities for Reducing Volcanic Risk through Land Use Planning in New Zealand", *The Australasian Journal of Disaster and Trauma Studies*, No. 1.

Bevington, J. et al. (2010), "Uncovering Community Disruption Using Remote Sensing: As Assessment of Early Recovery in Post-Earthquake Haiti", University of Delaware, Disaster Research Center, Delaware.

Bolton, D. K. and M. A. Friedl (2013), "Forecasting Crop Yield Using Remotely Sensed Vegetation Indices and Crop Phenology Metrics", *Agricultural and Forest Meteorology*, Vol. 173, pp. 74–84.

Bradshaw, S. (2004), "Socio-Economic Impacts of Natural Disasters: A Gender Analysis", p. 57.

Brown, D. L. et al. (2010), "Disaster Recovery Indicators: Guidelines for Monitoring and Evaluation".

Burton, C. G. (2012), "The Development of Metrics for Community Resilience to Natural Disasters", Doctoral Dissertation, University of South Carolina.

Chan, J. C.-W. and D. Paelinckx (2008), "Evaluation of Random Forest and Adaboost Tree-Based Ensemble Classification and Spectral Band Selection for Ecotope Mapping Using Airborne Hyperspectral Imagery", *Remote Sensing of Environment*, Vol. 112, No. 6, pp. 2999–3011.

Chen, T. and C. Guestrin (2016), "XGBoost: A Scalable Tree Boosting System", *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16, ACM, New York, NY, USA, pp. 785–794.

Chen et al. (2003), "Damage Pattern Mining in Hurricane Image Databases", *Proceedings Fifth IEEE Workshop on Mobile Computing Systems and Applications*, presented at the Proceedings Fifth IEEE Workshop on Mobile Computing Systems and Applications, pp. 227–234.

Combest-Friedman, C. et al. (2012), "Household Perceptions of Coastal Hazards and Climate Change in the Central Philippines", *Journal of Environmental Management*, Vol. 112, pp. 137–148.

Davies, M. et al. (2009), "Climate Change Adaptation, Disaster Risk Reduction and Social Protection: Complementary Roles in Agriculture and Rural Growth?", IDS Working Paper, No. 320, Institute of Development Studies.

Del Rosario, E. D. (2013), "Final Report Re Effects of Typhoon "Yolanda" (Haiyan)", Report, National Disaster Risk Reduction and Management Council (NDRRMC), Quezon City, Philippines.

Duarte, D. et al. (2018), "Satellite Image Classification of Building Damages Using Airborne and Satellite Image Samples in a Deep Learning Approach", *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. IV–2, pp. 89–96.

Ebert, A. et al. (2009), "Urban Social Vulnerability Assessment with Physical Proxies and Spatial Metrics Derived from Air- and Spaceborne Imagery and GIS Data", *Natural Hazards*, Vol. 48, No. 2, pp. 275–294.

Edenhofer, O. (Ed.) (2014), *Climate Change 2014: Mitigation of Climate Change; Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, New York, NY.

Field, C. B. and IPCC (Eds.) (2012), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, Cambridge, 1. publ.

Flax, L. K. et al. (2002), “Community Vulnerability Assessment Tool Methodology”, *Natural Hazards Review*, Vol. 3, No. 4, pp. 163–176.

Friedman, J. H. (2001), “Greedy Function Approximation: A Gradient Boosting Machine”, *The Annals of Statistics*, Vol. 29, No. 5, pp. 1189–1232.

Garcia Schustereder, M. et al. (2016), “Donor-Assisted Land-Use Planning in the Philippines: Insights from a Multi-Level Survey”, Deutsches Evaluierungsinstitut der Entwicklungszusammenarbeit (DEval), Bonn, p. 84.

Georganos, S. et al. (2018), “Very High Resolution Object-Based Land Use–Land Cover Urban Classification Using Extreme Gradient Boosting”, *IEEE Geoscience and Remote Sensing Letters*, Vol. 15, No. 4, pp. 607–611.

Gevaert, C. M. et al. (2017), “Informal Settlement Classification Using Point-Cloud and Image-Based Features from UAV Data”, *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 125, pp. 225–236.

GFDRR (2017), “Philippines”, *Global Facility for Disaster Reduction and Recovery*, *https://www.gfdrr.org/philippines*.

Ghaffarian, S. et al. (2018), “Remote Sensing-Based Proxies for Urban Disaster Risk Management and Resilience: A Review”, *Remote Sensing*, Vol. 10, No. 11, pp. 1–30.

GIZ (2014), “Results Chain - Environment and Rural Development Program (Based on Amended Offer, Version - February 3, 2014)”.

Gorelick, N. et al. (2017), “Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone”, *Remote Sensing of Environment*, Big Remotely Sensed Data: tools, applications and experiences, Vol. 202, pp. 18–27.

Government of the Philippines (2010), “Philippine Disaster Risk Reduction and Management Act of 2010. Republic Act No. 10121.”

Jha, S. et al. (2018), “Natural Disaster, Public Spending, and Creative Destruction: A Case Study of the Philippines”, ADBI Working Paper Series, No. 817, Asian Development Bank Institute (ADBI).

Kerle, N. (2015), “Disasters: Risk Assessment, Management, and Post-Disaster Studies Using Remote Sensing”, in Thenkabail, P. S. (ed.), *Remote Sensing of Water Resources, Disasters, and Urban Studies*, Boca Raton, Florida, pp. 455–482.

Kerle, N. et al. (2019), “Evaluating Resilience-Centered Development Interventions with Remote Sensing”, *Remote Sensing*, Vol. 11, No. 21, p. 2511.

Kerle, N. and R. R. Hoffman (2013), “Collaborative Damage Mapping for Emergency Response: The Role of Cognitive Systems Engineering”, *Natural Hazards and Earth System Sciences*, Vol. 13, No. 1, pp. 97–113.

Kohli, D. et al. (2012), “An Ontology of Slums for Image-Based Classification”, *Computers, Environment and Urban Systems*, Vol. 36, No. 2, pp. 154–163.

Kohli, D. et al. (2013), “Transferability of Object-Oriented Image Analysis Methods for Slum Identification”, *Remote Sensing*, Vol. 5, No. 9, pp. 4209–4228.

Kuffer, M. et al. (2016), “Slums from Space - 15 Years of Slum Mapping Using Remote Sensing”, *Remote Sensing*, Vol. 8, No. 6, p. 455.

Lagmay, A. M. and N. Kerle (2015), “Storm-Surge Models Helped for Hagupit: Typhoons”, *Nature*, Vol. 519, No. 7544, pp. 414–414.

Lech, M. et al. (2018), “Improving International Development Evaluation through Geospatial Data and Analysis”, *International Journal of Geospatial and Environmental Research*, Vol. 5, No. 2.

Leppert, G. (2015), *Social Risk Management Strategies and Health Risk Exposure: Insights and Evidence from Ghana and Malawi*, Lit Verlag, Münster.

Leppert, G. et al. (2018), "Impact, Diffusion and Scaling-Up of a Comprehensive Land-Use Planning Approach in the Philippines. From Development Cooperation to National Policies", German Institute for Development Evaluation (DEval), Bonn.

Li, X. et al. (2018), "Long-Term Monitoring of the Impacts of Disaster on Human Activity Using DMSP/OLS Nighttime Light Data: A Case Study of the 2008 Wenchuan, China Earthquake", *Remote Sensing*, Vol. 10, No. 4, p. 588.

Löw, P. (2018), "Hurricanes Cause Record Losses in 2017 - The Year in Figures", *Munich RE*, *https://www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/2017-year-in-figures.html*.

Matthews, T. (2012), "Responding to Climate Change as a Transformative Stressor through Metro-Regional Planning", *Local Environment*, Vol. 17, No. 10, pp. 1089–1103.

Mboga, N. et al. (2017), "Detection of Informal Settlements from VHR Images Using Convolutional Neural Networks", *Remote Sensing*, Vol. 9, No. 11, p. 1106.

Morrow, B. H. (1999), "Identifying and Mapping Community Vulnerability", *Disasters*, Vol. 23, No. 1, pp. 1–18.

MSU-Iligan Institute of Technology et al. (2015), "The Comprehensive Land Use Plan of Iligan City and the Disaster Risk Reduction and Management Framework of the Philippines", *Journal of Government and Politics*, Vol. 6, No. 1, pp. 115–124.

Mulla, D. J. (2013), "Twenty Five Years of Remote Sensing in Precision Agriculture: Key Advances and Remaining Knowledge Gaps", *Biosystems Engineering*, Vol. 114, No. 4, pp. 358–371.

Newell, B. et al. (2005), "A Conceptual Template for Integrative Human-Environment Research", *Global Environmental Change*, No. 15, pp. 299–307.

Platt, S. et al. (2016), "Measuring Resilience and Recovery", *International Journal of Disaster Risk Reduction*, Vol. 19, pp. 447–460.

Ren, X. et al. (2017), "A Novel Image Classification Method with CNN-XGBoost Model", in Kraetzer, C., Y.-Q. Shi, J. Dittmann and H. J. Kim (eds.), *Digital Forensics and Watermarking*, Springer International Publishing, Cham, Vol. 10431, pp. 378–390.

Rubin, C. B. et al. (1985), "Community Recovery from a Major Natural Disaster", FMHI Publications, Louis de la Parte Florida Mental Health Institute (FMHI), Florida.

Shackleton, S. et al. (2014), "A Gendered Perspective of Vulnerability to Multiple Stressors, Including Climate Change, in the Rural Eastern Cape, South Africa", *Agenda*, Vol. 28, No. 3, pp. 73–89.

Sliuzas, R. and M. Kuffer (2008), "Analysing the Spatial Heterogeneity of Poverty Using Remote Sensing: Typology of Poverty Areas Using Selected RS Based Indicators", in Carsten, J. (ed.), *Remote Sensing - New Challenges of High Resolution EARsel Joint Workshop Bochum (Germany), March 5-7, 2008*, Bochum, Germany.

Toye, J. (2017), *The Many Faces of Socioeconomic Change*, Oxford, UK.

Turner, B. L. et al. (2003), "A Framework for Vulnerability Analysis in Sustainability Science", *Proceedings of the National Academy of Sciences*, Vol. 100, No. 14, pp. 8074–8079.

Vetrivel, A. et al. (2018), "Disaster Damage Detection through Synergistic Use of Deep Learning and 3D Point Cloud Features Derived from Very High Resolution Oblique Aerial Images, and Multiple-Kernel-Learning", *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 140, pp. 45–59.

Villanueva, P. S. (2010), "Learning to ADAPT: Monitoring and Evaluation Approaches in Climate Change Adaptation and Disaster Risk Reduction – Challenges, Gaps and Ways Forward", SCR Discussion Paper, No. 9, Institute for Development Studies (IDS); Christian Aid; Plan International, Brighton, UK.

Yilmaz, S. and V. Venugopal (2013), "Local Government Discretion and Accountability in Philippines", *Journal of International Development*, Vol. 25, No. 2, pp. 227–250.

Zhang, F. et al. (2016), "Scene Classification via a Gradient Boosting Random Convolutional Network Framework", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 54, No. 3, pp. 1793–1802.

7. ANNEX

Annex A: Specifications and Acquisition Times of the Images Used for Proxy Extraction

Study area	Satellite	Acquired date	Spatial resolution	
			Multispectral image (m)	Panchromatic image (m)
Tacloban	WorldView2	2013-03-17	2	0.5
Tacloban	WorldView2	2017-03-18	2	0.5
Tacloban	GeoEye1	2013-11-10	2	0.5
Tacloban	GeoEye1	2013-11-12	2	0.5
Tacloban	GeoEye1	2013-11-13	2	0.5
Tacloban	GeoEye1	2016-04-24	2	0.5
South Leyte	WorldView2	2013-03-25	2	0.5
South Leyte	WorldView2	2013-04-02	2	0.5
South Leyte	WorldView2	2014-01-07	2	0.5
South Leyte	WorldView2	2014-07-16	2	0.5
South Leyte	WorldView2	2014-09-11	2	0.5
South Leyte	WorldView2	2014-10-21	2	0.5
South Leyte	WorldView2	2014-12-01	2	0.5
South Leyte	WorldView2	2016-01-24	2	0.5
South Leyte	WorldView2	2016-06-24	2	0.5
Basey	WorldView2	2013-05-18	2	0.5
Basey	WorldView2	2013-05-18	2	0.5
Basey	WorldView2	2013-09-01	2	0.5
Basey	WorldView2	2013-11-19	2	0.5
Basey	WorldView2	2013-11-21	2	0.5
Basey	WorldView3	2014-12-09	1.3	0.31
Basey	WorldView3	2015-01-10	1.3	0.31
Basey	WorldView2	2016-06-04	2	0.5
Basey	WorldView2	2016-06-04	2	0.5
Lawaan	WorldView2	2013-05-18	2	0.5
Lawaan	WorldView2	2013-05-18	2	0.5
Lawaan	WorldView2	2014-01-07	2	0.5
Lawaan	WorldView2	2014-01-07	2	0.5
Lawaan	WorldView3	2014-10-07	1.3	0.31
Lawaan	WorldView2	2015-11-24	2	0.5

Source: own figure.