International Journal of Disaster Risk Reduction 60 (2021) 102285

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Agent-based modelling of post-disaster recovery with remote sensing data

Saman Ghaffarian [a,*], Debraj Roy [b], Tatiana Filatova [b,c], Norman Kerle [a]

[a] Department of Earth System Analysis (ESA), Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, 7500 AE, Enschede, the Netherlands

[b] Department of Governance and Technology for Sustainability, University of Twente Drienerlolaan, 5, Enschede, 7522 NB, the Netherlands

[c] PERSWADE Research Center, School of Information, Systems and Modeling, Faculty of Engineering and IT, University of Technology Sydney, 15 Broadway, Ultimo, NSW, 2007, Australia

A R T I C L E I N F O

Keywords:
Post-disaster recovery
Resilience
Agent-based model
Remote sensing
Philippines
Machine learning

A B S T R A C T

Disaster risk management, and post-disaster recovery (PDR) in particular, become increasingly important to assure resilient development. Yet, PDR is the most poorly understood phase of the disaster management cycle and can take years or even decades. The physical aspects of the recovery are relatively easy to monitor and evaluate using, e.g. geospatial remote sensing data compared to functional assessments that include social and economic processes. Therefore, there is a need to explore the impacts of different dimensions of the recovery, including individual behaviour and their interactions with socio-economic institutions. In this study, we develop an agent-based model to simulate and explore the PDR process in urban areas of Tacloban, the Philippines devastated by Typhoon Haiyan in 2013. Formal and informal (slum) sector households are differentiated in the model to explore their resilience and different recovery patterns. Machine learning-derived land use maps are extracted from remote sensing images for pre- and post-disaster and are used to provide information on physical recovery. We use the empirical model to evaluate two realistic policy scenarios: the construction of relocation sites after a disaster and the investments in improving employment options. We find that the speed of the recovery of the slum dwellers is higher than formal sector households due to the quick reconstruction of slums and the availability of low-income jobs in the first months after the disaster. Finally, the results reveal that the households' commuting distance to their workplaces is one of the critical factors in households' decision to relocate after a disaster.

1. Introduction

Annually natural disasters take a high toll in terms of assets and people globally. Between 1998 and 2017 the number of affected people increased from 4 to more than 5.7 billion people [1,2], imposing US$ 520 billion of damages in real annual global economic costs [2,3]. This escalation is due to the accelerated urbanization and the increase in the number and severity of natural disasters that accelerate with climate change. However, these losses are not equally distributed across countries. Low-income countries incurred substantially higher Gross Domestic Product (GDP) losses over the past 20 years due to natural disasters when compared to high-income countries [2]. The rapid increase in disaster severity and frequency and associated damage calls for effective disaster risk reduction and management strategies at different scales, including individual actions.

One of the main phases of the disaster risk management cycle is the recovery phase, which usually starts after the operations for the response phase have concluded, and whose effectiveness has a significant effect on the final disaster cost. Post-disaster recovery (PDR) is known as a process to rebuild the community to normal conditions/functioning level, i.e. the same as before the disaster. However, it is essential to use the recovery process as an opportunity to rebuild the affected area better as per the Sendai Framework [4]. This framework was adopted at the third United Nations world conference on disaster risk reduction in Sendai, Japan, on March 2015, and outlines seven goals and four action priorities to prevent and reduce disaster risks. One of the priorities is to improve disaster preparedness through the building back better concept in the recovery phase, resulting in more resilient and sustainable communities [4,5]. This becomes vital where the vicious cycle of disasters weakens affected areas, setting them up for rapid follow-on disasters [6,7]. Nevertheless, recovery is a dynamic process that varies in duration and quality [8]. Furthermore, a holistic recovery process goes beyond a

* Corresponding author. Business Economics and Information Technology Groups, Wageningen University & Research, the Netherlands.
E-mail addresses: saman.ghaffarian@wur.nl (S. Ghaffarian), d.roy@utwente.nl (D. Roy), t.filatova@utwente.nl (T. Filatova), n.kerle@utwente.nl (N. Kerle).

https://doi.org/10.1016/j.ijdrr.2021.102285
Received 11 August 2020; Received in revised form 25 April 2021; Accepted 25 April 2021
Available online 5 May 2021

physical recovery of infrastructure and includes a re-establishment of social, economic, and natural environmental processes [9]. Hence, it involves multiple sectors, governmental departments, policymakers, and households working together. This makes recovery a complex process. Therefore, there is a need for monitoring and providing tools for decision-makers to collect information about the ongoing PDR process and understand the effect of different scenarios in dynamics. Evaluating the PDR can give valuable information to the decision-makers regarding the current stage of the process, useful for monitoring and comparison with the envisioned recovery plans [10–13].

Increasingly, there is a need to understand and explore the impacts of different dimensions of recovery, including the behaviour of individual actors and their interactions with socio-economic institutions. Computer-based simulations such as agent-based models (ABMs) permit to explore the dynamics of the recovery process from the bottom up. ABMs are computational models of societies where different actors – households, firms, farmers, governments – act, learn, interact, and coevolve with their environment [14]. In an ABM, agents (decision-making entities) interact with each other and their environments to decide and act based on defined rules for their behaviour in a specific situation such as a PDR [15,16]. ABMs, which simulate paths between equilibria and emergence of new post-disaster states, generate a wider range of nonlinear behaviour than conventional models that focus on the recovery as the 'return to normality'. Therefore, it constitutes an opportunity for policy-makers to test different policy scenarios in an artificial simulation environment and explore their consequences [17]. Accordingly, policy and decision-makers can take advantage of the simulation outcomes to steer the recovery process.

Remote sensing (RS) is the science of obtaining information about objects and features on earth surface through analyzing the data acquired by sensors without being in contact with them. RS as a rapid and effective tool to collect geospatial data have been used for different purposes in the DRM domain [11–13,18,19]. Brown et al. [8] used indicator-based methods to monitor and evaluate the post-disaster recovery based on high-resolution remote sensing imagery, in addition to field surveys and internet-based statistic data sets. They extracted physical information form RS data such as land cover changes, and building-based reconstruction. Burton et al. [20] used repeat photography to evaluate post-Katrina recovery in Mississippi. They took photographs every six months over a three-year period. Then, by assigning scores to each scene in terms of change and recovery, they generated a map for recovery assessment for the entire region. Wagner et al. [21] used medium resolution images to capture the rate of recovery for post-tornado sites in Oklahoma in 1990. They used remote sensing images to support government and decision-makers by monitoring reconstruction processes. They showed the importance and efficacy of using RS data for recovery assessment. Also, recent advances in machine learning/computer vision methods and computer hardware have increased the accuracy and speed of the semi/automatic approaches in the extraction of information from RS data [10,22–25]. For instance, Sheykhmousa, et al. [13] used support vector machines classifier to produce land cover and land use maps from very high resolution satellite images, and evaluate the recovery by extracting the changes in the maps. Ghaffarian et al. [25] developed an approach to monitor the recovery processes in large scale using random forest classifier within a cloud computing platform, i.e., Google Earth Engine. Deep learning techniques as advanced machine learning methods were also used to extract damages to buildings and infrastructures [22,26,27], and update the building maps [24]. They demonstrated the efficiency of using machine learning methods in extracting information from RS data in an automatic manner to support post-disaster recovery management. The integration of RS with machine learning can provide a powerful tool to monitor physical recovery; however, it is also essential for an effective recovery management to understand and extract the socio-economic reasons behind the processes. ABMs are used frequently in the disaster management domain [28–33] such as flood management [34,35], disaster evacuation modelling [36,37], coastal adaptation [38], disaster impact assessment [31,39,40], recovery modelling [41–43] and resilience assessment [42,44,45]. The response phase management and evacuation after a disaster have been extensively addressed in the literature [33,36,37,40]. However, PDR management as a long-term process has not yet been sufficiently studied to extract the influential factors and their impacts on this process. As one of the initial ABM-based studies in post-disaster recovery, Nejat and Damnjanovic [46] developed a spatial-temporal ABM based on the dynamic homeowners' interactions with their neighbours in a post-disaster recovery situation. They showed that the discount factor (i.e., the weight of homeowners' utility from reconstruction) and the accuracy of the signals (i.e. the owners' future reconstruction property value) have impacts on the reconstruction of the houses. However, their model only focuses on housing recovery/reconstruction without including the individual personal factors/attributes. Afterwards, researchers tried to add individual personal behaviours to ABM for different purposes and applications for the recovery process. Kanno et al. [47] developed an ABM framework for the simulation of the post-disaster recovery in urban systems, with a final goal of disaster resilience assessment. In their ABM, they defined agents representing the behaviour of the civil life, production industry, and infrastructures to understand their impact on the recovery and resilience. Their results showed that each of the subsystems has an impact on the resilience (i.e., the action or act of rebounding or springing back) of the urban systems with different coefficients/weights. In another study, tourist recovery strategies were studied using ABM after an earthquake in Jiuzhai Valley, China (in August 2017) [48]. Their model provides a tool for managers to have an overall estimation of future tourist decline, as well as economic losses during the post-earthquake recovery period. Coates et al. [49] developed an ABM to assess the flood recovery and preparedness adaptation measures for small and medium-sized enterprises. They mainly studied physical and social adaptation factors and showed their combined significance effects in the adaptation of a key industrial area of the UK for a severe flooding scenario. In a different study, an ABM was developed to support sustainable disaster recovery by adding the environmental vulnerability to the model, and thus the decision-making process. The model was used to improve the community's welfare by reducing the vulnerability of the area to disasters and increasing the residents' needs/objective function (e.g. income and monthly distributed tax amount) [50]. In addition, Moradi and Nejat [51] developed an ABM to identify pre-disaster mitigation needs through predicting the possible outcomes of different plans in recovery phase. They showed that adding spatial information to ABM for recovery decision making is crucial still post-disaster recovery ABM commonly simulate entire communities, ignoring decision traits that may vary among low and high-income households. Furthermore, while geo-referenced data is frequently used in ABMs [52,53], the ABMs focused on PDR underutilize the power of RS data. Rarely such ABMs would use a time series of RS images to inform or validate the model, especially for the Global South DRM research. Yet, RS promises a great support in complementing other socio-economic data sources especially in such data-poor regions by revealing the areas impacted by a disaster, their physical recovery patterns and indirectly even data on socio-economic inequality like differences in formal and informal settlements.

This article presents an ABM to explore the post-disaster recovery process (the PDR ABM) in the presence of various policy scenarios. We apply the model to Tacloban, the Philippines, which was hit by super Typhoon Haiyan in 2013. The innovative contribution of this article is four-fold. Firstly, RS data are employed as the main data source to initialize and validate the PDR ABM and the reconstruction of the built-up area in the recovery process directly by extracting physical aspects of the process [13,24] or indirectly using proxies to conduct functional recovery assessments [11,13]. In our study, RS data are used to extract multi-temporal land use maps, including slum and formal building information, using advanced machine learning methods. Secondly, we differentiate between the behaviour of formal and informal (slum) sector households, which follow different decision-making strategies in the recovery process. The outputs of the model and the multi-temporal utility satisfaction can serve to evaluate the disaster resilience of these target groups. This also allows us to go beyond the physical aspects and explore the socio-economic factors of the PDR dynamics. Thirdly, the spatial distribution of the households utility satisfaction is visualized and overlaid with the high-resolution satellite images that add the capability of exploring the spatial recovery patterns. Hence, the article also has a purpose of illustrating the utility of combining multi-temporal RS data and ABM. Fourthly, we use the developed model to run two realistic policy scenarios: the construction of relocation sites after a disaster and the investments in improving employment options. In what follows we describe the methodology and the case-study, present the simulation results and discuss them in the context of disaster risk and resilience management.

2. Methods

2.1. Case-study and data

Tacloban city, located in the Eastern Visayas, is the biggest city and the economic centre of the Leyte region in the Philippines (Fig. 1). The city has a population of approximately 250.000, with an economy largely focused on commerce, agriculture, fishing, industry (mostly palm oil factories), tourism, and trade. There are formal and informal (slums, mostly stretched along the coast) neighbourhoods in the city, showing the socio-economic diversity of the population. On the November 8, 2013, Tacloban was hit by Typhoon Haiyan (locally known as Typhoon Yolanda), which was one of the strongest typhoons ever to make a landfall worldwide [54]. The occurrence of a storm surge of up to 5 m led to an official fatality number of 6201 for the city, mostly killing people who lived in the coastal neighbourhoods [55].

Using the RS data (i.e. high-resolution satellite images) we can extract the built-up areas, including slum and formal buildings, of the city before the disaster and trace the recovery process in the first years following Haiyan. To explore the social processes driving this recovery, we developed the PDR ABM, parameterized with the maps extracted from the RS data. Advanced machine learning methods [12,13] were employed to extract the land use maps from high-resolution satellite images through performing image classification (for the pre-disaster situation, as well as three days, three months, and eight months after Haiyan) (Table 1). We followed a standard framework to classify the images and produce land use maps from satellite images using a machine learning method, same as implemented in Ref. [12]. The procedure starts with preparing the satellite images through implementing pre-processes such as geo-rectification, image mosaicking and extracting the region of interest. Then it continues with training area selection for the selected land use classes (e.g., formal and informal settlements) from the images, and extraction of important image features such as texture using image processing methods (i.e., local binary patterns). Final step is the execution of the machine learning method (i.e., Extreme Gradient Boosting algorithm [56]) to produce the land use maps for each time step. The land use raster maps of the region were converted to points with corresponding attributes as a Geographical Information System (GIS)[1] map of the urbanized region to be used in the model. Accordingly, informal and formal built-up areas were identified [12,13]. Also, the buildings damaged by Haiyan and the reconstruction levels of the area during the recovery process for each month were extracted from the land use maps. According to the results reported by Sheykhmousa et al. [13] on the reconstruction of the Tacloban area for four years after Haiyan and the best of our knowledge, we assumed that the modelled area had been fully reconstructed after five years.

Moreover, in 2015 we conducted extensive fieldwork in the area to understand how households made decisions and what impacted them. Specifically, we carried out interviews with key stakeholders, analyzed survey data (collected for the study [12]), and the demographic data collected from the Philippines Statistics Authority (e.g., employment rate, type of the economic activities before and after the disaster). The key persons, including authorities of the Tacloban city and a group of farmers and fishermen, were interviewed to understand the characteristics of the community, and how the disaster impacted them. Among others, the fieldwork revealed that immediately after Haiyan there was a relocation site developed in the northern part of Tacloban, aimed at becoming a safe area to move people out of danger zones, mostly slum dwellers. However, the relocation site was far from the city centre and the coast where most of the employment opportunities are located. We use the presence of the relocation site as well as the creation of additional employment opportunities as scenarios in the PDR ABM.

2.2. Agent-based modelling of post-disaster recovery

We developed a spatial ABM to simulate the decision-making process of individuals in a post-disaster recovery process in a city. The PDR model provides a tool to understand how households (living in informal or formal settlements) change jobs and locations to live after a disaster, driven by primary factors that influence their decisions during the reconstruction process. Appendix A provides a detailed description of the model according to the ODD + D protocol [57]. Here we briefly outline the main agents, the rules guiding their choices and the overall flow of the model.

The main agents in the PDR ABM are households and buildings in an urban environment. There are two types of households: those residing in formal (FH) or informal (IH) urban areas that have different behaviours mostly due to their economic and education level. Hence, IH/FH label different socio-economic groups which are characterized by different attributes, including the location within formal (for FH households) or informal (for IH households) urban areas. Further, households can be heterogeneous within each group, differentiated by income, education and workplace. Buildings in the modelled city can be for residential (formal or informal) and industrial use. Industrial buildings, important as they represent the location of mid- and high-income jobs, usually accessible only for FH with a higher level of education compared to IH. IH, which reside in slums, often have jobs in an informal sector, such as in fishing or as a seasonal labourer in the agricultural sector. Accordingly, households agents aim to satisfy their utility in the model by choosing where to live and what job to take (Fig. 2).

Currently, the PDR ABM is applied to several neighbourhoods in Tacloban and heavily relies on empirical data as explained in 2.1 and Appendix A. Households' utility is shaped by agents' social and economic needs (i.e. job, education, income, accessibility to the workplace). These factors help to assess how satisfied an agent is with living in a particular location, and having/lacking a job, the match between its income and education level, and the commute to its workplace. The utility $U(A_i)$ of an agent (A_i) can be computed based on its current living and working state using the following equation:

$$U(A_i) = I * J * \left(\frac{Y}{E}\right) * (1 - D) \tag{1}$$

where I represents the impact of the disaster, J shows the job status, Y and E are the income and education levels, respectively, and D is the normalized distance to the workplace for each agent (more details regarding the variables of the utility are provided in Appendix).

Taking an action changes individual agent utility. The utility of an agent depends on its socio-economic and personal expectations defined by the agent's social level (i.e. education level). This utility expresses how satisfied an agent is with living in a particular location, and having/

[1] Geographical Information System (GIS) is a tool to map, analyse, and visualize remote sensing and spatial data.

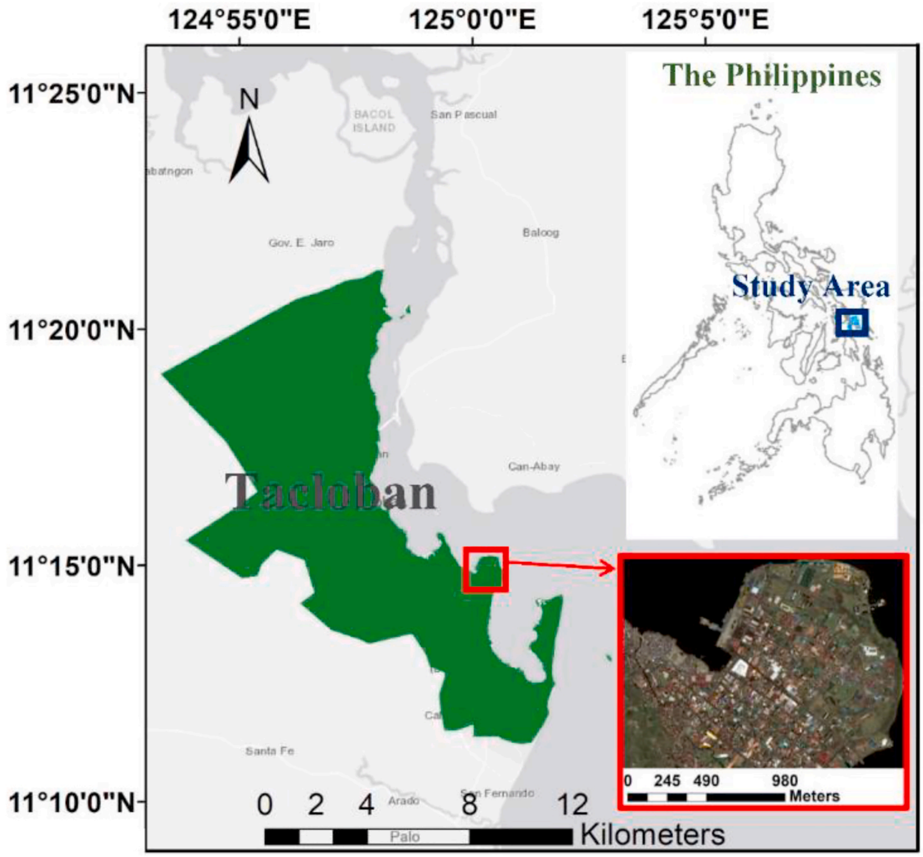


Fig. 1. The overview of Tacloban, the Philippines, and the satellite image for the modelled urban area acquired before Haiyan.

Table 1
Satellite images used in this study.

ID	Timeline	Acquired date	Satellite platform	Description
T0	Before Haiyan	2013-03-17	WorldView-2	Pansharpened images with 0.5 m spatial resolution
T1	Event time	2013-11-11	WorldView-2	
T2	Post-Haiyan 1	2014-01-25	Pleiades	
T3	Post-Haiyan 2	2014-06-16	Pleiades	

not having a job, the balance between its income and education level, and which workplace it has to commute to each day for work. Though agents try bounded rationality: while they prefer an action that improves their utility, they are not searching for a global maximum. Such actions include: relocating their place of residence, changing a job, or both combined.

The agent can change its job or location consulting its social network or by searching among available options individually. To define the social network and agent interactions in the PDR model we employ the theory of homophily [58,59], in which the social network is based on the degree of similarity (homophily) between two agents (more details in Appendix A.iv). To do so, we first determine the contact network and collect the information (using Eq. A.2), then the agent selects through the available opportunities provided by the networks. In the PDR model, the degree of homophily is computed based on the similarity of the three agent attributes: job category/workplace, education, and income level (Eq. A.3). As a proxy for the accessibility analysis in the PDR model, we employed the distance to the workplace, which was computed from the RS data (please refer to Appendix A for details). Based on our interviews, we assume that IHs prefer to live near their workplaces, having therefore a short daily commute.

The PDR model is initialized using the point-based land use data (FH, IH, and location of the industrial workplaces). Since the aim of this study is to investigate the utility of combining RS data and ABM to show the process of recovery while testing real scenarios, and due to the availability of the multi-temporal RS data and census data, we developed the model for the business district of Tacloban city, where typhoon Haiyan caused massive damages (Fig. 1). In total, the agents are randomly assigned to 2131 informal residential and 1703 formal housing areas at initialization. The agents' state variables for individual IH and FH households are derived from the land use map of the Tacloban urban area, key interviews, census data, and survey data as described in Appendix (Table A. 1). The PDR model started from one month before Haiyan and evolved with a time step equal to one month. Hence, the PDR model started in September 2013 with a total of 11,502 agents.

During each step of the recovery phase in the PDR ABM, a damaged building may be reconstructed or a new one added to the residential building stock for agents to live in. The monthly increase of the reconstructed buildings was extracted separately for formal buildings and slums using the machine learning-derive land use maps from the satellite images (see 2.1).

3. Results and discussion

Our PDR ABM simulates the post-disaster recovery to explore the recovery patterns of formal sector households and slum dwellers. Their differences affect decision making during the recovery process. We focus specifically on the effects of relocation site existence after a disaster and the dynamics of the employment rate in the model. In some post-disaster cases, such as in Tacloban, based on the hazard exposure and vulnerability measurements, governments decide to relocate people from high

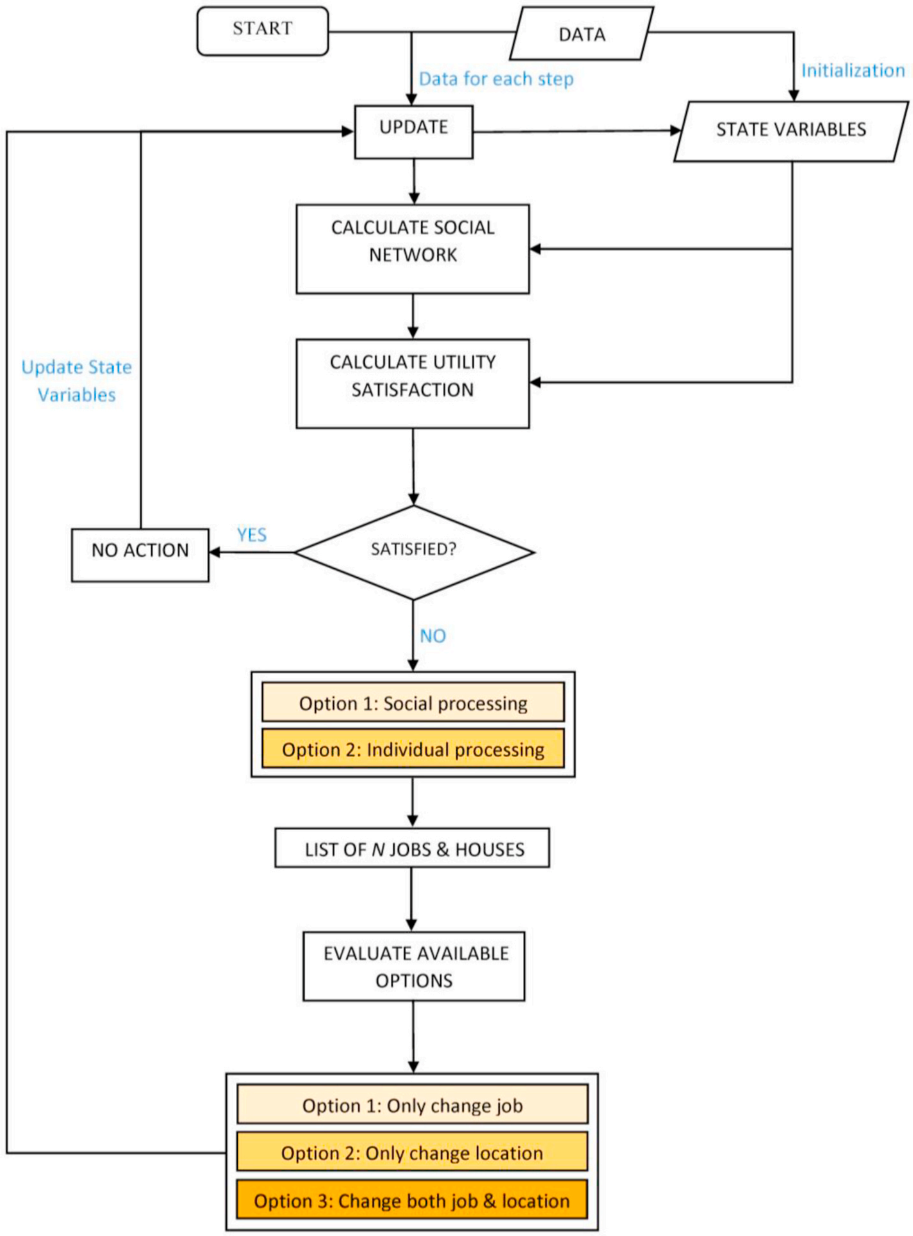


Fig. 2. Conceptual flow framework of the PDR ABM.

natural hazard risk to safer zones; however, this policy is not always successful. To model this policy scenario, we added a new residential area – built in the Tacloban case – as formal houses to the model that becomes accessible after the disaster, which is far from central urban areas. As a second policy scenario, we consider a boost in the job recovery commonly supported by NGOs in disaster-impacted areas. Having a job is key for individual welfare and socio-economic resilience in every society. Hence, we assess the impacts of changing employment rates on the recovery process and the resilience for both IH and FH by changing the employment rate while the other parameters are fixed. Furthermore, we calculate the recovery rate by dividing the utility satisfaction level at any stage of the recovery by its corresponding pre-disaster one.

The model was executed 30 times for each of the experiments under the same parameter combinations. We present the mean and standard deviation values of households' utility satisfaction across the 30 model runs. Since this metric is computed based on the socio-economic status of the households (e.g., income and education level) as well as the physical recovery rate (i.e., reconstruction of the buildings), it provides a holistic overview of the recovery status of the households (please refer to Appendix A. for more details). Socio-economic factors deriving the micro-level households' choices are based on the insights from our 2015 field work and open-ended interviews with Tacloban citizens from various occupations. In addition to this qualitative micro-validation at the agent level, we perform the macro validation of the simulated spatial patterns of recovery against the actual recovery patterns from the time series of RS data. These macro-level patterns have underlying social dynamics which we reconstruct in our PDR ABM. Validation in this case refers to the ability of model heuristics to generate patterns observed in the data [53,60]. However, since RS data capture only the physical aspects of the recovery – damage and reconstruction of buildings – and not the utility satisfaction of individual households, a macro validation of this socio-economic dimension was not feasible given the available data.

3.1. Post-disaster recovery patterns

We implement the PDR model based on the available data and the information collected using both machine learning-derived information from RS images and census data. The PDR model results are employed to show and discuss the recovery patterns of the IH and FH in the urban area of Tacloban after Haiyan for the first 18 months after the disaster. Fig. 3 shows the mean satisfaction of the IH and FH starting from before the disaster (step = 0), and immediately after the disaster (step = 2), and then during the post-disaster recovery process. Indeed, this figure illustrates the post-disaster recovery curve of the area in terms of the utility satisfaction of the households. The increasing speed of the IH satisfaction in the early recovery phase (in the first four months) is higher than the one with FH, indicating that the IH is more resilient than the FH in terms of coming back to the same utility satisfaction levels. Yet, it does not necessarily demonstrate that IH is indeed more resilient since the original state was not, to begin with. In addition, the recovery rates of the IH and FH are 97% and 103%, where above 100% shows the better mean utility satisfaction than pre-disaster situation, and thus, reaching the build-back-better goal. The speedy recovery of slum dwellers occurs due to two main reasons: (1) slums were reconstructed much faster than the formal buildings since it is easier to build a slum dwelling compared to a formal structure, this is also observed by analyzing the satellite images; (2) availability of low-income jobs is higher than high-income jobs in the early recovery phase, and the IH are more easily satisfied even with lower-income occupations due to their generally low education level. At the same time FHs prefer to have high-income jobs, given their education level. Yet, the large industries and factories – which most of the FHs prefer as a workplace offering higher-incomes – take more time to reconstruct after a disaster.

Fig. 4 illustrates the spatial distribution of the mean utility satisfaction of the households for pre-disaster (step = 0), just after the event (step = 2), 3 (step = 5), 8 (step = 10), and 17 (step = 19) months after the disaster. The areas denoted with a circle are informal settlements/slums, which recovered faster than the area denoted with a rectangle, which is formal settlements.

Fig. 5 illustrates the dynamics in the percent of HHs working in high income and low-income jobs during the recovery. The results show an increase in HHs working in low-income jobs after the disaster (step = 1 is the disaster moment) due to destruction of the high-income job places (e.g. factories) and FH (highly educated households) work in low-income jobs. However, by progressing with the reconstruction of the industrial buildings those FH have come back to high-income jobs to increase their utility satisfaction.

3.2. Planned relocation and individual choices in the post-disaster recovery process

One of the policies that have already been implemented in Tacloban is to move people away from the coastal strip, which is highly exposed to Typhoon-related hazards such as high winds and storm surges, to a relocation site in the designated safe zone North of Tacloban. Planned relocation is a top-down policy to intentionally move urban developments out of the hazard zones, for example by using public funds to rebuild housing in safe areas or by offering financial incentives for people to relocate from hazard hot spots. However, this can be affected by individual choices which are the bottom-up actions of the households such as choice of a location to live (e.g., returning back to the same house or moving to another place). Hence, we tested the scenario of having such a relocation site in the PDR model and to assess the effect of commuting distance in the post-disaster recovery process. We did this by adding new and available residential areas after the disaster only for slum households, the same as the actual policy in Tacloban. However, the distance to work (i.e. IH workplaces e.g. fishing) for IH who reside in this relocation site increases (i.e. 0.9 as the normalized distance to the workplace in the city), and has a significant impact on households' utility. Fig. 6 shows the recovery curve (based on mean utility) of the FH and IH after the disaster. Accordingly, the results show that IHs recover faster in the early recovery phase by having an option of accommodation after the disaster; however, after two to three months the presence of relocation site has a low impact on the speed or quality of the recovery, but rather producing almost the same change in utility of the IH. In addition, the recovery rates of the IH and FH are 102% and 109%, where above 100% shows the better mean utility satisfaction than pre-disaster situation, and thus, reaching the build-back-better goal.

The spatial distribution of the mean utility for IH and FH with relocation site availability after the disaster is generated and overlaid on the original image of the area for the pre-disaster and post-disaster periods (Fig. 7). Moreover, the number of relocation site dwellers was computed for each of the selected steps and is illustrated for each step

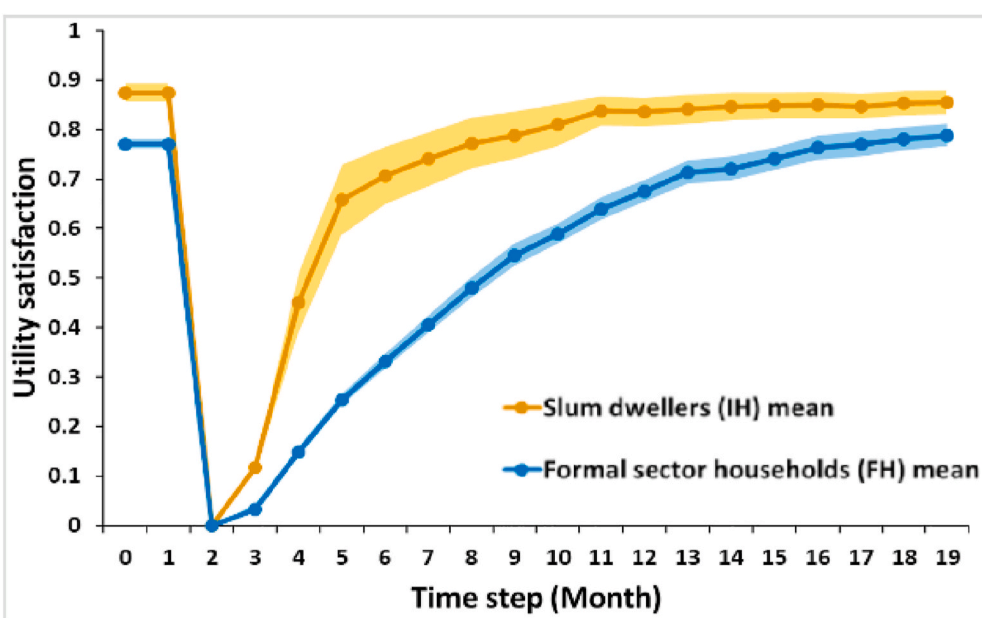


Fig. 3. Mean and standard deviation utility satisfaction of the households residing in formal (FH) and informal (IH) urban areas for different time steps in the model, in which each step is equal to a month and the time step = 1 is the Haiyan disaster moment.

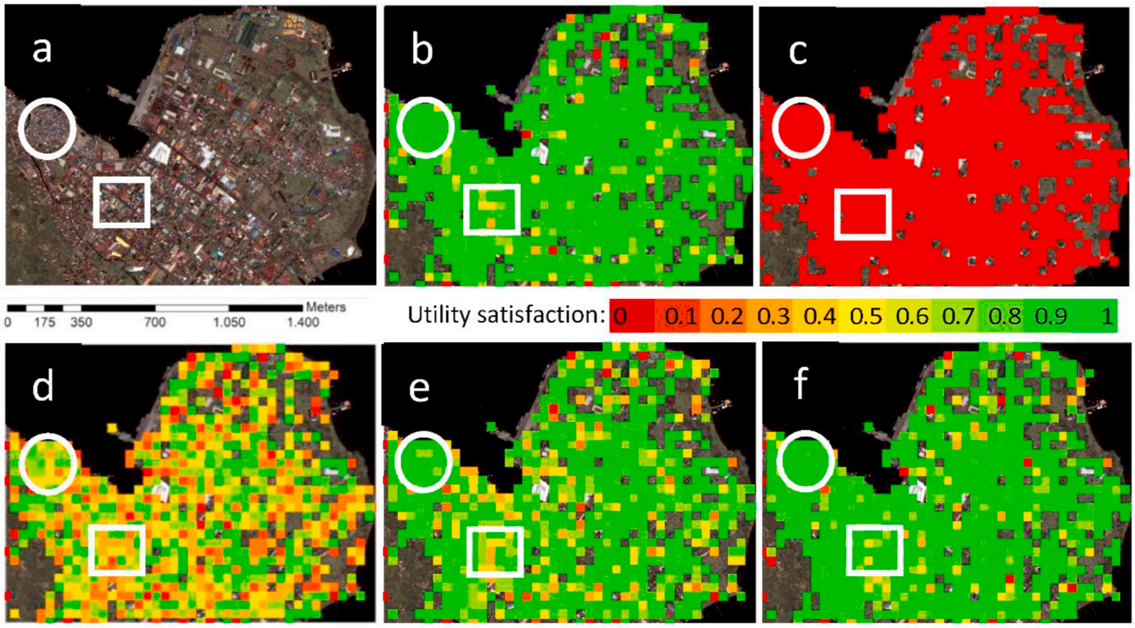


Fig. 4. (a) Pre-Haiyan high-resolution satellite image of central Tacloban, (b–f) spatial distribution of the mean utility satisfaction for households living in informal (denoted by a circle) and formal (denoted by rectangle) settlements for steps 0, 2, 5, 10, and 19, respectively. Each time step is equal to a month; the typhoon Haiyan hits the area on step = 1 of the simulation.

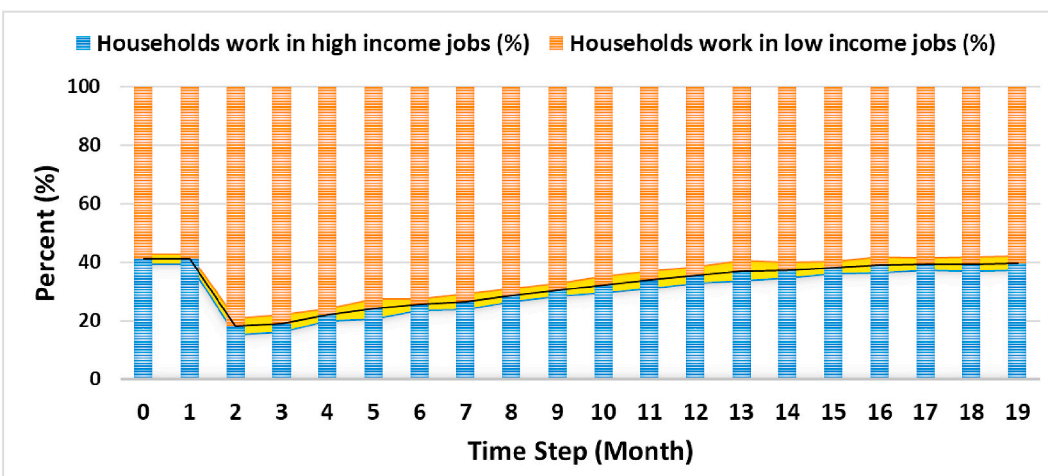


Fig. 5. Percent of Household agents employed at high income (blue) versus low-income (orange) jobs in the post-disaster recovery process. Each time step is equal to a month; the typhoon Haiyan hits the area on step = 1 of the simulation.

(Fig. 7i). The results demonstrate the pattern of IH movement into and out of the relocation site in the post-disaster recovery period. Accordingly, IHs moved to the relocation site in the early recovery phase, where they do have at least houses to live in, and consequently, this increases their satisfaction. However, by progressing with the reconstruction process in the central part of the Tacloban, the occupation ratio of the relocation site is decreased (Fig. 7). This shows that IHs prefer to move back to the same locations as the pre-disaster situation, which are closer to their workplaces, and this is an important factor in increasing their satisfaction. Accordingly, policy and decision-makers should consider the commute distance to workplaces as one of the influential factors in planning the recovery, in particular new settlement constructions, while trying to increase the resilience of the households by decreasing the hazard exposure and vulnerability.

3.3. The effect of the employment rate on the post-disaster recovery process

In the PDR model, the employment rate determines the probability of an agent having a job, which also has an impact on the calculation of agents' utility satisfaction (Appendix A. Eq.1). The utility satisfaction of an agent without a job will be zero, and it will look for new job opportunities or a new location and a job. This also becomes important in a post-disaster situation, in which there are job dynamics, and an agent may use its social contact network or individual processing to find a job based on its characteristics. According to the official statistics data (explained in section 2.1) for Tacloban, the employment rate in 2012 (pre-disaster) was 0.92. However, the employment in the post-disaster situation is contingent on the financial aid received from national governments and international NGOs, expanding the range of feasible recovery pathways. Hence, we ran a sensitivity analysis changing the

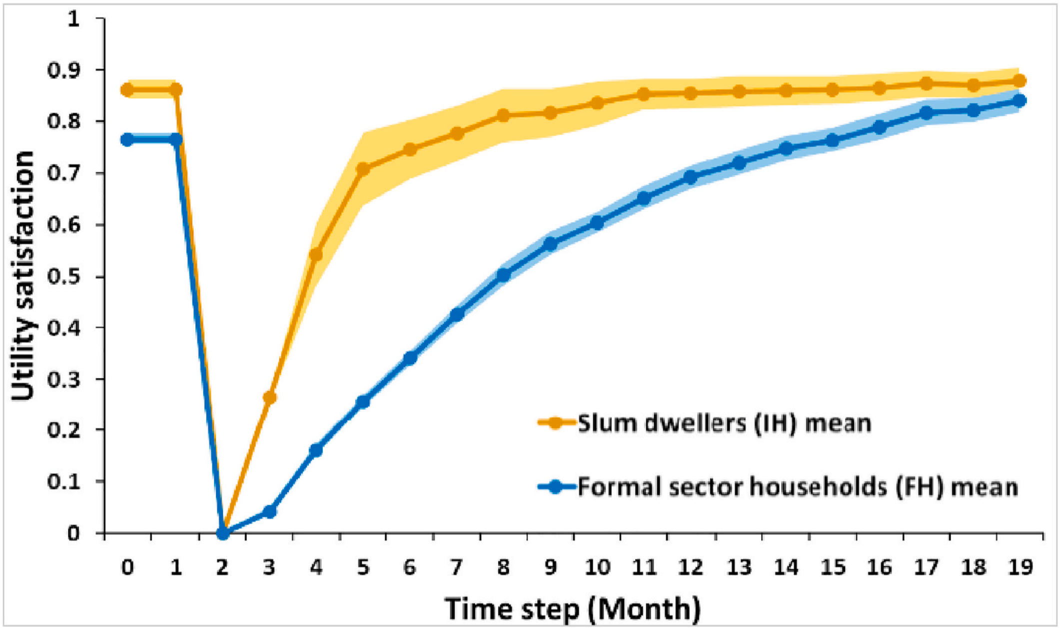


Fig. 6. Mean and standard deviation utility satisfaction of the households residing in formal (FH) and informal (IH) urban areas for different time steps with the presence of relocation site. Each time step is equal to a month; the typhoon Haiyan hits the area on step = 1 of the simulation.

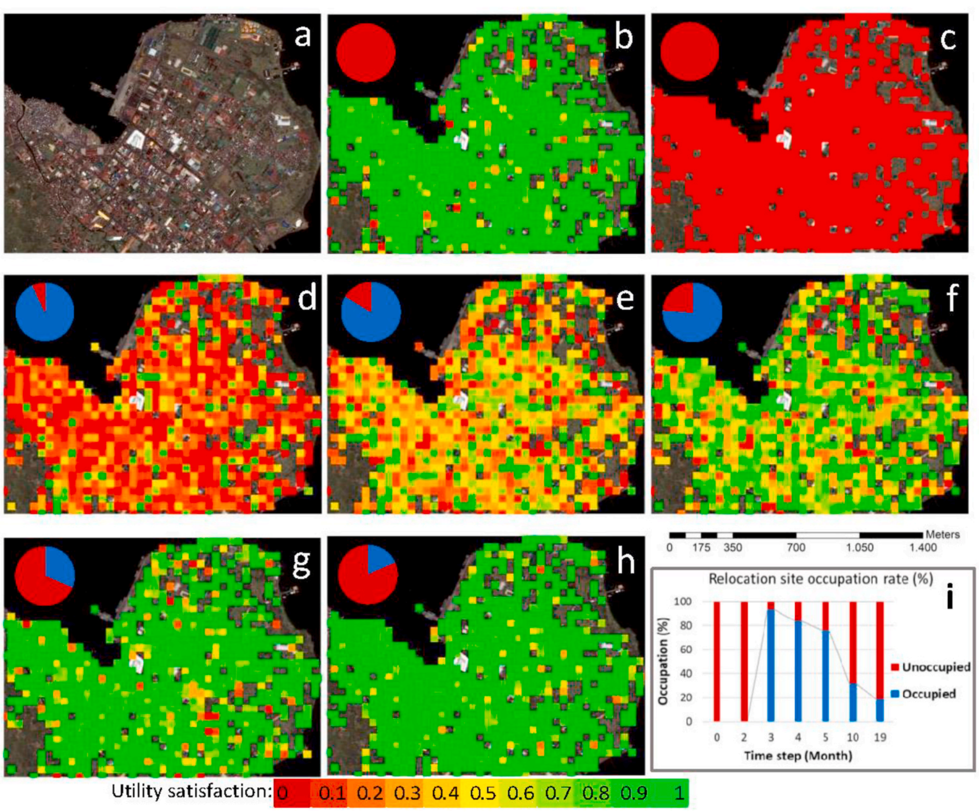


Fig. 7. (a) Pre-Haiyan high-resolution satellite image of Tacloban urban area, (b–h) spatial distribution of the mean utility satisfaction of households residing in formal (FH) and informal (IH) settlements for steps 0, 2, 3, 4, 5, 10 and 19, respectively; the pie-chart here denotes the occupation ratio of the relocation site at steps 0, 2, 3, 4, 5, 10 and 19, respectively, and (i) is the relocation site occupied and unoccupied ratio for pre- and post-disaster situations. Each time step is equal to a month; the typhoon Haiyan hits the area on step 1 of the simulation.

employment rate [0.5; 0.7; 0.8] in addition to the actual rate (i.e. 0.92) to explore its effect on the post-disaster recovery process. As before, we report the dynamics of utility satisfaction unfolding during the recovery for IHs and FHs separately (Fig. 8). The results demonstrate that the FH and IH recover (i.e. return to almost normal utility satisfaction) after the disaster at almost the same speed. Moreover, the IH recovery rates with the employment rates of 0.5, 0.7, 0.8, and 0.92 are respectively 99%, 98%, 104%, and 97%, and the FH recovery rates with the employment rates of 0.5, 0.7, 0.8, and 0.92 are respectively 104%, 103%, 104%, and 103%. The above 100% recovery rates show the better mean utility satisfaction than pre-disaster one, and thus, reaching the build-back-better goal.

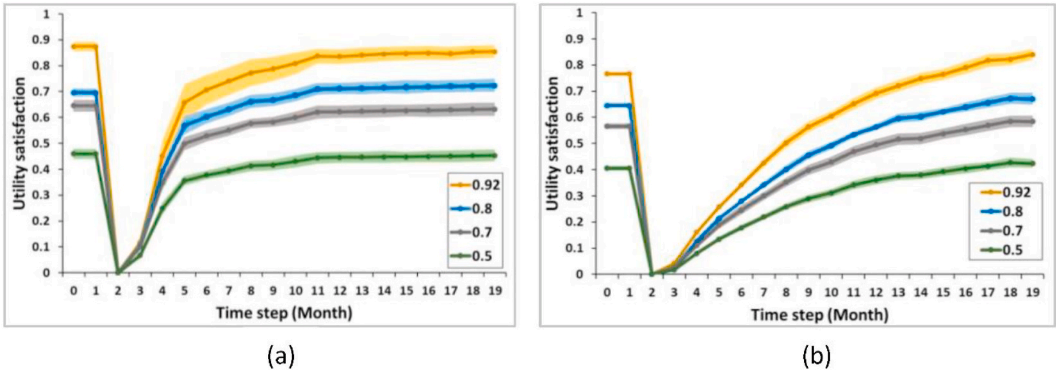


Fig. 8. The temporal evolution of the mean and the standard deviation of utility satisfaction of households residing in formal (a) and informal (b) settlements under the assumption of different employment ratios (0.5, 0.7, 0.8, 0.92). Each time step is equal to a month; the typhoon Haiyan hits the area on step = 1 of the simulation. .

4. Conclusions

In this paper, we develop a spatial ABM of post-disaster recovery to explore the behaviour of two distinct groups living in a city, i.e. families residing in the formal and informal urban areas. The urban area of the Tacloban city, the Philippines, which hit by Typhoon Haiyan on 8th November in 2013, is used as a case study to define the characteristics of the agents and create the environment. The objective of the study is to go beyond the physical assessment of the recovery process and investigate how different areas of the impacted city recover and how this recovery process unfolds for various socio-economic groups. To address this challenge, we investigate the recovery patterns of formal and informal settlements separately, and explore the dynamics of households' utility comprised of satisfaction by their location and job. The latter is an emergent property of the model, driven by incremental decisions of individual heterogeneous households whose bounded-rational choices depend on own socio-economic factors and peer influence via social network. We have integrated multi-temporal RS data and advanced machine learning methods to provide input to the ABM. To do so, we model the behaviour of heterogeneous households who aim to satisfy their utility shaped by the individual socio-economical characteristics. We present the simulation results for two groups: slum dwellers (IH) and households residing in formal housing (FH).

The main findings of this paper are the following: (i) it adds new understanding of the PDR patterns of the formal and informal households by modelling their behaviour as heterogeneous individuals interacting in the spatial landscape; (ii) the developed new visualization technique based on integration of the PDR ABM outputs with high resolution satellite images (i.e., overlaying the model outputs on RS images) provides insights into understanding the spatial patterns of the recovery; (iii) this study explores emergence of recovery patterns resulting from the decision-making process of formal and informal households in the presence of hazard-free relocation sites after a disaster and a change in employment options.

Based on the insights gained from the PDR model we identify that IH recovers faster than FH and therefore, may appear more resilient. However, we question whether returning to the same state – which was already undesirable to begin with for IH – is ethically-acceptable in the presence of such inequalities, and runs counter to Sendai principles. Slum-dwellers suffer the most extensive damage during the disaster and develop no capacity to recover to a better state, even in the presence of new housing in a safe zone if it robs them of employment opportunities. It is also shown that this type of visualization provides insights into the neighbourhood level assessments, which can also be employed for other applications. To gain more insights and detailed information regarding the behaviour of the IH and FH groups, we define and test two policy scenarios: the construction of the relocation site and impact of the employment rate change on the recovery process and resilience of the households. We show that while the existence of a relocation site increased the IH recovery speed and thus their resilience, the employment rate has a small effect on the speed of the recovery for both IH and FH in terms of utility satisfaction measure. Furthermore, we demonstrate the importance of the commute distance to the workplace for IH.

The results show that the basic aim of developed PDR model has been reached since it provides insight into different recovery patterns of the slum and formal sector households. Therefore, policymakers and governments can use the insights derived from the model to understand recovery rates at the neighbourhood level. However, detailed data (e.g., micro-level survey data) are needed to replace the randomness/stochasticity in the model and understand the behaviour of various individuals and their dynamics during the recovery.

One of the limitations of this study is neglecting the effect of the natural hazard risk and risk perception of the individuals after such a major disaster. Hence, by adding the natural hazard risk components (e.g. exposure to hazard, vulnerability and prior disaster experience) to the PDR model, more accurate empirical implementation of the model can be obtained. Some of the information related to these components can also be extracted from RS data, but it would primarily rely on households' surveys. Furthermore, the PDR ABM is used to test the effect of employment rate assuming that it is constant during the simulation. However, this rate is dynamic and it might change even more after a disaster. Hence, further work is required to explore the effect of such dynamic ratio on the recovery process, calling for further empirical data collection on the socio-economic side. Moreover, adding more variables/components to utility measure of the PDR model, such as social and economic characteristics of households (e.g., age and gender), can provide more insights into the socio-demographic inequalities in the recovery process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The satellite images were provided by the European Space Agency, and Digital Globe Foundation, which was granted for a project at ITC entitled "Post-disaster recovery assessment using remote sensing data and spatial economic modelling". The Survey data were provided by the German Institute for Development Evaluation (DEval), Competence Centre for Evaluation Methodologies, Bonn, Germany. This work was partially supported by the European Research Council (ERC) under the

European Union's Horizon 2020 Research and Innovation Program (grant agreement number: 758014).

Appendix A. The ODD + D description of the PDR agent-based model

In this section, we describe the developed post-disaster recovery (PDR) model based on the ODD + D protocol [57]. The ODD + D provides a standard description and documentation protocol for agent-based models, which guides researchers to sufficiently substantiate their model.

a. Overview

i. Purpose

The developed post-disaster recovery (PDR) model simulates the decision-making process of individuals with respect to spatial mobility and job dynamic/selection based on the satisfying individual utility according to socio-economic parameters for the households in urban areas of Tacloban, the Philippines. The PDR model provides a tool to understand how households (living in informal or formal settlements) select/change jobs and locations after a disaster during the reconstruction processes, based on the primary factors that influence their decisions after the disaster. In addition, the variable recovery across different neighbourhoods/sections of an affected urban area can be revealed by processing RS data; however, there is a need for effective tools to explain those observations and identify suitable means to influence the recovery process (find bottlenecks, etc.). The PDR model allows studying the different recovery rates of urban areas. Accordingly, policymakers and governments can use the insights derived from the model to understand why some regions may thrive and others languish (formal and informal settlements) and make effective decisions during the post-disaster recovery process.

ii. Entities, state variables, and scales

The main agents in the PDR model are households and buildings in an urban environment. Households could be of two types: families residing in formal (FH) or informal (IH) urban areas that have different behaviours, mostly due to their economic and education level. Further, households can be heterogeneous within each group, differentiated by income, education, workplace. Urban buildings could be of residential formal or informal and industrial buildings. The PDR model distinguishes between two types of residential areas – formal and informal (slums) as well as industrial buildings. The latter is important as they represent the location of mid- and high-income jobs, usually accessible only for FH with a higher level of education compared to IH. IH often have jobs in an informal sector, such as fishing or seasonal agricultural sector labour. The time interval of the model after the disaster is defined as a month.

iii. Process overview and scheduling

The overall process of the model is based on satisfying individual utility by choosing an action that gives them higher utility (Fig. 2). This is derived from the agent's social and economic needs, which also defines the behaviour of the agent in the model. Let $(U(A_i))(i = 1, 2, 3, \ldots, N)$ represent the utility level of the agent, where N is the number of agents, and (A_i) is based on its current state in the model, then it will look for possible actions (options) (a_i) to change its state and increase the current utility level. The possible actions for the agent (A_i) are to move to a new location or changing its job, or both move to a new location and change its job. The agent can change its job or location using its social network or by looking for a list of available options individually. The lower utility level of an agent derived from its current state when compared to the others increases the chance of taking one of the possible actions in the model and changing its state. Accordingly, the information/state of the agent (a_i) will be updated to its selected action from the previous step. Then, the utility $(U(a_i))$ is calculated using the updated state of the agent based on the selected new action. The higher calculated utility from its current one will lead to taking action and change in the information of the agent for the next step.

b. Design concepts

i. Theoretical and empirical background

- **Theoretical background:** The agent behaviour in the PDR model is firmly embedded in the choice theory [61], urban economics [62], and sustainable livelihoods approach [63]. Lancaster [64] defined the utility function $U_{in} = U(x_{in})$, where x_{in} is the vector of the attributes for alternatives (such as workplace accessibility in a particular location [62]) i by every agent n. Recent studies [59,65] have confirmed that workplace accessibility is an influential factor in households' location choices. After a disaster, the importance of workplace accessibility was highlighted in field interviews [12], as some buildings and infrastructure may be destroyed, forcing households to relocate or change jobs. Ben-Akiva and Bierlaire [66] expanded the utility function to incorporate variability in population: $U_{in} = U(x_{in}, s_n)$, where s_n is a vector of different agent characteristics, for example, income, education, and employment. We employed the workplace distance as a proxy for the accessibility and income, education, and employment (characteristics of the agent) in the PDR model. We used it to compute the utility satisfaction $(U(A_i))$ (see Eq. (1)). Further, we validated the choice of attributes through field interviews in the disaster region.

The concept of social capital explains/defines the benefits of the contact networks between households and different social groups based on their social ties that can provide information regarding the opportunities in the communities [63]. This means that households can have an impact on each other's decisions. In addition, social networks are one of the influential factors of individual activities in the community after a disaster and in the recovery phase by sharing the information in their social networks [67]. The similarity (homophily) and interactions between individuals are one of the important factors in making the connections and creating social contact networks [58,59]. Hence, we employed the theory of homophily in the PDR model to define agent interactions. To do so, we first determined the contact network and then selected the information with the agent to select through the available opportunities provided by the networks.

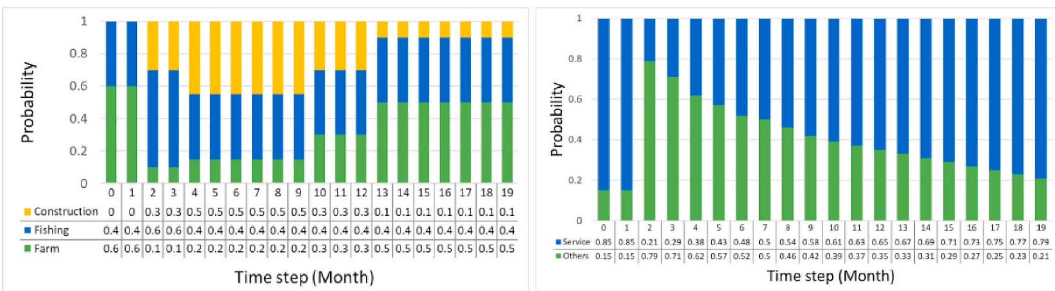
- **Empirical background:** We used two information/data sources in the PDR model (explained in section 2.1): 1- Fieldwork data: key interviews, survey data (collected for the study [12]) and the demographic data collected from the Philippine Statistics Authority (e.g., unemployment rate, type of the economic activities before and after the disaster), 2- RS data, in particular, high-resolution satellite images acquired during pre- and post-disaster times. We extracted information from the machine learning-derived land cover, and land use maps using multi-temporal satellite images (the pre- and three days after disaster land use maps produced by Ref. [13]) to be used in the PDR model.

ii. Individual decision making

The decision making of an agent *(A_i)* relies on satisfying own utility *$U(A_i)$* based on its current state with respect to living and working environment. Taking an action *(a_i)* changes individual agent utility. The utility of an agent *(A_i)* depends on its socio-economic and personal expectations defined by the agent's social level (i.e. education level). This utility expresses how satisfied an agent is with living in a particular location, and having/not having a job, the balance between its income and education level, and which workplace it has to commute to each day for work. Accordingly, the utility for each agent can be computed using the following equation (A1):

$$U(A_i) = I^* J^* \left(\frac{Y}{E}\right)^* (1 - D) \tag{A1}$$

where *I* represents the impact of the disaster, *J* shows the job status, *Y* and *E* are the income and education levels, respectively, and *D* is the normalized distance to the workplace for each agent *(A_i)*. Each variable of the utility can be determined as follow:



(a) (b)

Fig. A1. The probability distribution of the job sectors for IH (a) and FH (b) over time. Each time step is equal to a month, and step = 1 is the disaster moment.

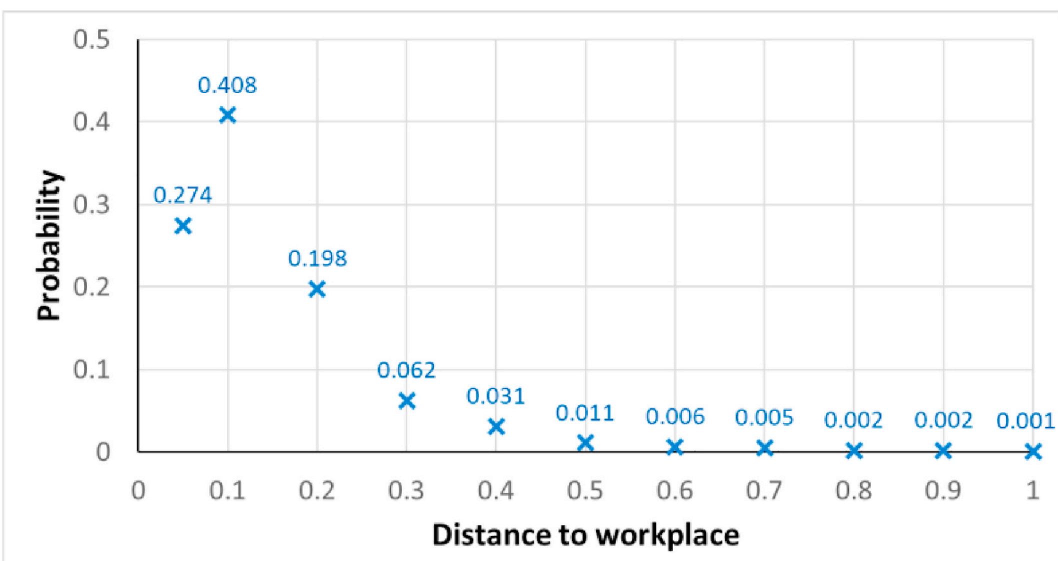


Fig. A2. The probability distribution of the distance to the workplace (i.e. service job type) for FHs.

- *I*: shows if the agent has been impacted by the disaster and its house has been damaged or even destroyed. Thus, if the agent has a house damaged/destroyed $I = 0$, and if not $I = 1$. The damaged and intact buildings were extracted using RS-derived land use maps (explained in section 2.1).
- *J:* if the agent has a job $j = 1$, and if not $j = 0$. The job options for the highly educated households/agents (FH) are services (which are considered high-income jobs), farm, fishing, construction (which are in the group of low-income jobs). However, IH agents can only work in low-income jobs. The selection of the unemployed agents is made based on the probability distribution, which is extracted from the data. Accordingly, the probability of having a job for each agent is 0.92 (i.e., employment rate extracted from census data), while the probability of not having a job is 0.08.
- *Y:* there are two income levels in the model: low and high. For an agent with high-income $Y = 1$, and with low-income $Y = 0.5$. Service sector employment falls in the high-income job group, while farm, fishing, and construction are in the low-income job category. Hence, FH agents prefer to work in high-income jobs, given that they are highly/better-educated agents, and IH can only work in low-income jobs. Assigning a workgroup to an agent is also based on the distributions extracted from data (Fig. A1).
- *E:* there are two education levels in the model. For an agent with high education level $E = 1$, and with low education level $E = 0.5$.

- *D:* is the distance to workplaces for the agents. The distance for FHs is based on the distribution that has been computed from the RS data (Fig. A2). This distance was initially computed in a point-to-point manner using the pre-Haiyan land use map (using FH and industrial buildings locations/ coordinates). Also, IHs work in low income jobs (e.g., farming, fishing) and according to our observations and the data collected during the fieldwork they mostly reside close to their workplaces (e.g., farmland) in Tacloban. Thus, for IHs, the distance to workplaces can be either 0.05 or 0.1 based on equal distribution.

Based on the above-explained variables and their possible values, the utility of the agent will be [0,1]. For example, an agent without a house to live (when its house was destroyed by the disaster and has not yet been reconstructed in the recovery phase) or a job to have income, or has a workplace in the farthest place its $U(A_i)$ will be equal to zero.

Each step of the model is considered as one month, and during the recovery phase, the buildings might be reconstructed and can be added to the model, i.e. can be used for agents to live in. The monthly increase of the reconstructed buildings was extracted separately for formal buildings and slums using the machine learning-derive land use maps from satellite images (explained in Section 2 - Methods).

iii. Individual sensing

The social contact network of each agent can be formed based on their social interactions in the social spaces like community centres and workplaces [65,68–71]. Accordingly, we used the workplace of agents as a space to make the contact network in the model. First, we used the following equation (A2) to find the degree of the potential of being a contact network:

$$C(A_i,\ A_j) = Sector(A_i,\ A_j) + \gamma \tag{A2}$$

where $Sector(A_i,\ A_j)$ is equal to one if the agents work in the same business sector, and if not it equals to zero. And, γ is a random number between zero and one and adds stochasticity in the model which is also observed in real world networks.

Past studies have shown that the random chance to form an edge in most social networks varies from 0.1 to 0.3 [72]. In this study, we have assumed a mean value of 0.2. Then finally, the agents A_i and A_j may become a contact network and may have an impact on each other's decisions if $C(A_i,\ A_j)$ has a greater number than 0.8.

iv. Interactions

This section describes how the agents in their contact network (which are extracted using the previous section) make social networks and share information and opportunities in the model. To do so, we used the theory of homophily, in which the social network is based on the degree of similarity (homophily) between two agents. Accordingly, the agents with similar attributes have a higher degree of homophily and have more social impact on each other. This theory has been validated in several studies that use different attributes (e.g., age, education language) of the individuals in the social network [58,73,74]. In addition, it has also been used for defining the social network for slum dwellers [59].

In the PDR model, the degree of homophily is computed based on the similarity of the three agent attributes: job category/workplace, education, and income level. And it can be formulated as follows (A3):

$$Hom(A_i, A_j) = \left|At_{A_i} \cap At_{A_j}\right| / \left|At_{A_i}\right| \tag{A3}$$

where $Hom(A_i, A_j) \in [0,1]$ is the degree of homophily with values closer to 1 indicating the higher degree of homophily, At_{A_i} and At_{A_j} are the set of attributes of the A_i and A_j, respectively. Hence, the weight of an edge between the agents A_i and A_j can be calculated using the equation below (A4):

$$\omega_e(A_i, A_j) = Hom(A_i, A_j) * \frac{d_{A_j}}{\sum_n d_{A_n}} \tag{A4}$$

where d_{A_j} is the degree of agent A_j (i.e., the number of links that the agent already possesses). Hence, based on the weight of edges for each agent, the household agents tend to copy attributes (i.e., job) of those agents with whom have a high homophily degree.

After computing the homophily degree for agent A_i and ranking them, the first five agents are selected as the most influential ones. Then, their edge weights are used in further steps to be copied/mimicked by agent A_i. However, due to the monthly change in the status of available jobs on a market during the recovery processes, the half weight of the influential agents is included in the model to account for the effect of the reconstruction process and job dynamics after the disaster.

v. Individual prediction

Each time step an individual/agent could change either his location or workplace or both. The change occurs only in the case of finding a new opportunity that increases his utility satisfaction. A decision to look for new opportunities is based on the individual threshold value drawn from the probability density function, which is based on the distribution of utility levels of all agents in the city achieved in the previous modelling step. This means that agents with utility lower than utility of the majority in the previous time step will have higher probability to seek new opportunities. We denote this threshold as T_{change} ranging from 0 to 1 for an agent A_i and draw it individually for each agent every time step to update the individual urge to look for new opportunities for changing agents' current states.

Then, if the utility value of the agent A_i is below the T_{change}, the agent will decide to gather information and look for updating/changing its current state and increase its utility satisfaction. There are three options to change for each agent (only change job, only change location, change both job and location), of which the agent randomly selects one based on the equal probability for each. After selection of each of which, the agent starts gathering information for undertaking a new action using one of the following ways:

- Individual processing: randomly evaluating N number of workplaces or locations or both from available options.
- Social networking: evaluating available options only for the workplace offered by its top N number of social contact networks.

Since the process of building reconstruction (including slums, formal and industrial buildings) changes the options available for the agents (workplace, household location) at each step, the reconstruction rate and job dynamics are the key components of the model (Fig. A3). Thus, individual processing is based on the updated information on the recovery. However, the social networking process for evaluating options uses information from the previous step. Hence, the PDR model only uses the half weight of the output of the social network added to the half weight of the updates that come from the reconstruction processes. Eventually, after evaluating all the options, the agent decides to undertake an activity only if this will increase its current utility level.

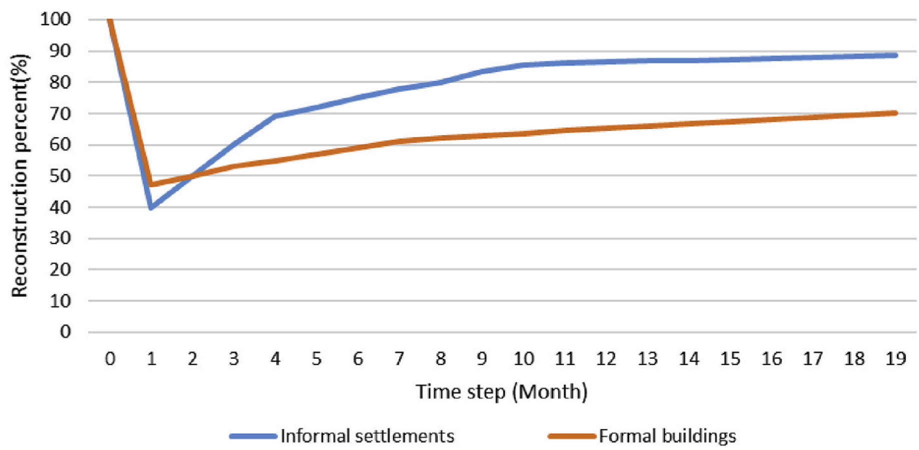


Fig. A3. Temporal evolution of the reconstruction percentage of the formal buildings (orange line) and informal settlements (blue line). Each time step is equal to a month; the typhoon Haiyan hits the area on step = 1 of the simulation.

vi. Collectives

Each agent (either FH or IH) collects and stores information about his social contact network.

vii. Stochasticity

The process of selection of the social contact network is stochastic due to including the randomly selected number for parameter γ. In addition, the decision making of the agents/individuals has a randomness selection procedure first to choose whether to change workplace or location or both together and then a random selection from the probability distribution of the available options. This procedure adds stochasticity to the decision-making process of the agents in the PDR model.

c. Details

The initialization of the model and the employed input data are described in this section. The PDR model was developed and executed in Python using the MESA framework, and the residential choice model developed by Ref. [59] was used as the base model. The source code is available on an open-access library for ABM, which can be downloaded using the following link: (https://github.com/Saman-Gh933/Agent-based-modeling-of-post-disaster-recovery-with-remote-sensing-data).

i. Initialization

The PDR model initialized using the point-based land use data (FH, IH and location of the industrial workplaces). In total, the agents randomly assigned to 2131 IH points and 1703 FH points are initialized in the model. The agents' state variables are individual IH and FH households derived from the land use map of the Tacloban urban area, key interviews, census data, and survey data (from Ref. [12]). The basic income and education levels of the agents for the pre-disaster time were extracted from RS-derived land use information. That means from the land-use map we extracted whether area is under formal or informal development, which we correspondingly link to residents with high and low-levels of income and education. If a household lives in an informal settlement, it has been categorized as having low income and low education levels; while, if a household lives in a formal settlement, then it presumably has a high income and education levels (Table A1). However, there are sub-groups for low-level income jobs, i.e. construction, fishing and farm (Fig. A1and Table A1, which are determined based on authors' knowledge gained from 2015 fieldwork. In addition, there is only one type of jobs for high-level income agents, i.e., services/high income industry. Notably, agents with high education level can also work in low-level income jobs, especially after the disaster. Yet, low-educated individuals cannot have high-income jobs (Fig. A1). Furthermore, the capacities for the houses and jobs were computed based on the population and employment rate for the barangays using census data and remote sensing-derived land use map. We find per barangay population in census data, and extract the number of grid cells for residential buildings from RS-derived land use maps for the corresponding barangay. Then, we extract the capacity of the residential building grid cell by dividing the population to the number of the residential building grid cells, the outcome value is three. Accordingly, each house in the formal and informal residential areas has the limit of three households. No limit was defined for low-income jobs in the informal sector according to census data and availability of many low-income jobs like fishing and farm. In contrast, the high-income job capacity is computed based on the population and employment rate. First, we extracted the number of households for the corresponding barangay, then multiply it with the employment rate, and finally divided the outcome by the number of the workplaces/buildings (as grid cell/pixel), and the final value is 3. Thus, the limit for the high-income job capacities is three. The PDR model started from one month before Haiyan to evolve. Hence, the PDR model started in September 2013 with a total number of 11,502 agents.

ii. Input data

There are two sources of the input data used in the model that change the conditions (available jobs, job types, and their probability distribution and open locations/houses) in each step. The damaged buildings and reconstruction levels of the built-up areas (slums and formal buildings) were extracted from the land use maps for three days after the disaster (for damage mapping and extracting the damaged houses), as well as three and eight months after the disaster. In addition, based on the best of our knowledge, we also assumed that the area had been fully reconstructed after five years. Subsequently, the extracted damage and reconstruction levels were transformed/translated to steps, given that each step of the model is one month.

Table A1
The key variables, their values and data sources used for the base PDR scenario.

Variable	Description	Initialization	Data used to extract
Household ID	Unique ID to identify a household	Randomly initialized in the model	–
Land use	To identify settlement type (i.e. formal or informal settlement)	Initialized using pre-disaster land use map	Remote sensing data
Impact of the disaster	Shows if the agent has been impacted by the disaster	Extracted using machine learning-derived post-disaster land use maps.	Remote sensing data
Job	Shows if the agent has a job	Randomly initialized using the unemployment rate.	Census data
Income	Income level of the agent	$Y = 1$ for high-level income, and $Y = 0.5$ for low-level income	Remote sensing data
Education	Education level of the agent	$E = 1$ for high level education, and $E = 0.5$ for low level education	Remote sensing data
Workplace	Workplace with the following possible choices: • Service/high-income industry • Farm • Fishing • Construction	Different business sectors were extracted using the survey data, and key interviews. And the location of the high-income job workplaces (i.e. service) was initialized using pre-disaster machine learning-derived land use map.	Survey data, Key interviews and remote sensing data
Distance to workplace	Commute distance to the workplace	For slum dwellers it is equal to 0.05 or 0.1, which is randomly initialized with equal probability distribution. For formal households it is computed from pre-disaster land use map which is ranging between [0.001, 0.408]	Remote sensing data

References

[1] CRED, The Human Cost of Natural Disasters, CRED, 2015.
[2] CRED, Economic Losses, Poverty and Disasters 1998-2017, CRED, 2018.
[3] T.W. Bank, Results Brief - Climate Insurance, 2017. Available at: https://www.worldbank.org/en/results/2017/12/01/climate-insurance.
[4] UNISDR, In Sendai framework for disaster risk reduction 2015 - 2030, in: Third World Conf. Disaster Risk Reduction, Sendai, Japan., 14-18 March, 2015, pp. 1–25. Sendai, Japan.
[5] K. Brundiers, H.C. Eakin, Leveraging post-disaster windows of opportunities for change towards sustainability: a framework, Sustainability 10 (2018) 1390.
[6] T. Alcayna, V. Bollettino, P. Dy, V. P, Resilience and disaster trends in the Philippines: opportunities for national and local capacity building, PLOS Currents Disasters (2016).
[7] T.W. Bank, Disaster Risk Management in the Caribbean: the World Bank's Approaches and Instruments for Recovery and Resilience, 2018.
[8] D. Brown, P. S, B. J, Disaster Recovery Indicators: Guidlines for Monitoring and Evaluation, CURBE, Cambridge University for Risk in the Built Environment: University of Cambridge, Cambridge, UK, 2010.
[9] MCDEM, Focus on Recovery: A Holistic Framework for Recovery in new zealand, MCDEM, New Zealand, 2005.
[10] S. Ghaffarian, N. Kerle, Post-disaster recovery assessment using multi-temporal satellite images with a deep learning approach, in: 39th EARSeL Conference, Salzburg, Austria., 2019.
[11] S. Ghaffarian, N. Kerle, T. Filatova, Remote sensing-based proxies for urban disaster risk management and resilience: a review, Rem. Sens. 10 (2018) 1760.
[12] N. Kerle, S. Ghaffarian, R. Nawrotzki, G. Leppert, M. Lech, Evaluating resilience-centered development interventions with remote sensing, Rem. Sens. 11 (2019) 2511.
[13] M. Sheykhmousa, N. Kerle, M. Kuffer, S. Ghaffarian, Post-disaster recovery assessment with machine learning-derived land cover and land use information, Rem. Sens. 11 (2019) 1174.
[14] F. Fiedrich, P. Burghardt, Agent-based systems for disaster management, Commun. ACM 50 (2007) 41–42.
[15] L. Tesfatsion, Agent-based Computationsl Economics: A Constructive Approach to Economic Theory, 2005.
[16] M. Wooldridge, An Introduction to Multi Agent Systems, Wiley, West Sussex, 2009.
[17] J.D. Farmer, D. Foley, The economy needs agent-based modelling, Nature 460 (2009) 685–686.
[18] S. Ghaffarian, N. Kerle, Towards post-disaster debris identification for precise damage and recovery assessments from uav and satellite images, Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. XLII-2/W13 (2019) 297–302.
[19] N. Kerle, F. Nex, M. Gerke, D. Duarte, A. Vetrivel, Uav-based structural damage mapping: a review, ISPRS Int. J. Geo-Inf. 9 (2019) 14.
[20] C. Burton, J.T. Mitchell, S.L. Cutter, Evaluating post-katrina recovery in Mississippi using repeat photography, Disasters 35 (2011) 488–509.
[21] M.A. Wagner, S.W. Myint, R.S. Cerveny, Geospatial assessment of recovery rates following a tornado disaster, IEEE Trans. Geosci. Rem. Sens. 50 (2012) 4313–4322.
[22] D. Duarte, F. Nex, N. Kerle, G. Vosselman, Multi-resolution feature fusion for image classification of building damages with convolutional neural networks, Rem. Sens. 10 (2018) 1636.
[23] A. Vetrivel, M. Gerke, N. Kerle, G. Vosselman, Identification of damage in buildings based on gaps in 3d point clouds from very high resolution oblique airborne images, ISPRS J. Photogrammetry Remote Sens. 105 (2015) 61–78.
[24] S. Ghaffarian, N. Kerle, E. Pasolli, J. Jokar Arsanjani, Post-disaster building database updating using automated deep learning: an integration of pre-disaster openstreetmap and multi-temporal satellite data, Rem. Sens. 11 (2019) 2427.
[25] S. Ghaffarian, A. Rezaie Farhadabad, N. Kerle, Post-disaster recovery monitoring with google earth engine, Appl. Sci. 10 (2020) 4574.
[26] A. Vetrivel, M. Gerke, N. Kerle, F. Nex, G. Vosselman, 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 J. Photogrammetry Remote Sens. 140 (2018) 45–59.
[27] A. Vetrivel, M. Gerke, N. Kerle, G. Vosselman, Identification of structurally damaged areas in airborne oblique images using a visual-bag-of-words approach, Rem. Sens. 8 (2016) 231.
[28] L. An, Modeling human decisions in coupled human and natural systems: review of agent-based models, Ecol. Model. 229 (2012) 25–36.
[29] T. Filatova, Market-based instruments for flood risk management: a review of theory, practice and perspectives for climate adaptation policy, Environ. Sci. Pol. 37 (2014) 227–242.
[30] T. Filatova, J.P.M. Mulder, A. van der Veen, Coastal risk management: how to motivate individual economic decisions to lower flood risk? Ocean Coast Manag. 54 (2011) 164–172.
[31] S. Mehvar, A. Dastgheib, T. Filatova, R. Ranasinghe, A practical framework of quantifying climate change-driven environmental losses (quanticel) in coastal areas in developing countries, Environ. Sci. Pol. 101 (2019) 302–310.
[32] J. Watts, R.E. Morss, C.M. Barton, J.L. Demuth, Conceptualizing and implementing an agent-based model of information flow and decision making during hurricane threats, Environ. Model. Software 122 (2019) 104524.
[33] Burger, Oz, Kennedy, Crooks, Computational social science of disasters: opportunities and challenges, Future Internet 11 (2019) 103.
[34] R.J. Dawson, R. Peppe, M. Wang, An agent-based model for risk-based flood incident management, Nat. Hazards 59 (2011) 167–189.
[35] Y.A. Abebe, A. Ghorbani, I. Nikolic, Z. Vojinovic, A. Sanchez, A coupled flood-agent-institution modelling (claim) framework for urban flood risk management, Environ. Model. Software 111 (2019) 483–492.

[36] X. Chen, F.B. Zhan, Agent-based modeling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies, J. Oper. Res. Soc. 59 (2008) 25–33.
[37] H. Wang, A. Mostafizi, L.A. Cramer, D. Cox, H. Park, An agent-based model of a multimodal near-field tsunami evacuation: decision-making and life safety, Transport. Res. C Emerg. Technol. 64 (2016) 86–100.
[38] D.E. McNamara, A. Keeler, A coupled physical and economic model of the response of coastal real estate to climate risk, Nat. Clim. Change 3 (2013) 559–562.
[39] A.Y. Grinberger, D. Felsenstein, Dynamic agent based simulation of welfare effects of urban disasters, Comput. Environ. Urban Syst. 59 (2016) 129–141.
[40] M. Markhvida, B. Walsh, S. Hallegatte, J. Baker, Quantification of disaster impacts through household well-being losses, Nature Sustainability 3 (2020) 538–547.
[41] M.S. Eid, I.H. El-Adaway, Optimizing disaster recovery strategies using agent-based simulation, in: Computing in Civil Engineering 2015, 2015, pp. 379–386.
[42] L. Sun, B. Stojadinovic, G. Sansavini, Agent-based recovery model for seismic resilience evaluation of electrified communities, Risk Anal. 39 (2019) 1597–1614.
[43] D. Mishra, S. Kumar, E. Hassini, Current trends in disaster management simulation modelling research, Ann. Oper. Res. 283 (2018) 1387–1411.
[44] R.J.K. Taylor, J. Forrester, G. Dreßler, S. Grimmond, Developing Agent-Based Models for Community Resilience: Connecting Indicators and Interventions, CRED, Louvain, 2015, p. 81.
[45] M. Boston, Z. Liu, C.C. Jacques, J. Mitrani-Reiser, In towards assessing the resilience of a community in seismic events using agent based modeling, in: Tenth U.S. National Conference on Earthquake Engineering, Anchorage, Alaska, U.S., Frontiers of Earthquake Engineering: Anchorage, Alaska, U.S, 2014.
[46] A. Nejat, I. Damnjanovic, Agent-based modeling of behavioral housing recovery following disasters, Comput. Aided Civ. Infrastruct. Eng. 27 (2012) 748–763.
[47] T. Kanno, S. Koike, T. Suzuki, K. Furuta, Human-centered modeling framework of multiple interdependency in urban systems for simulation of post-disaster recovery processes, Cognit. Technol. Work 21 (2018) 301–316.
[48] C. Fan, L. Gong, H. Li, An agent-based model approach for assessing tourist recovery strategies after an earthquake: a case study of jiuzhai valley, Tourism Manag. 75 (2019) 307–317.
[49] G. Coates, C. Li, S. Ahilan, N. Wright, M. Alharbi, Agent-based modeling and simulation to assess flood preparedness and recovery of manufacturing small and medium-sized enterprises, Eng. Appl. Artif. Intell. 78 (2019) 195–217.
[50] M.S. Eid, I.H. El-adaway, Sustainable disaster recovery: multiagent-based model for integrating environmental vulnerability into decision-making processes of the associated stakeholders, J. Urban Plann. Dev. 143 (2017), 04016022.
[51] S. Moradi, A. Nejat, Recovus: an agent-based model of post-disaster household recovery, J. Artif. Soc. Soc. Simulat. 23 (2020) 13.
[52] D.T. Robinson, D.G. Brown, D.C. Parker, P. Schreinemachers, M.A. Janssen, M. Huigen, H. Wittmer, N. Gotts, P. Promburom, E. Irwin, et al., Comparison of empirical methods for building agent-based models in land use science, J. Land Use Sci. 2 (2007) 31–55.
[53] A. Heppenstall, A. Crooks, N. Malleson, E. Manley, J. Ge, M. Batty, Future developments in geographical agent-based models: challenges and opportunities, Geogr. Anal. 53 (2021) 76–91.
[54] N. Mori, M. Kato, S. Kim, H. Mase, Y. Shibutani, T. Takemi, K. Tsuboki, T. Yasuda, Local amplification of storm surge by super typhoon haiyan in leyte gulf, Geophys. Res. Lett. 41 (2014) 5106–5113.
[55] P.K. Ching, V.C. de los Reyes, M.N. Sucaldito, E., T. An assessment of disaster-related mortality post-haiyan in tacloban city, Western Pac Surveill Response J 6 (2015).
[56] T. Chen, C. Guestrin, Xgboost: a scalable tree boosting system, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, San Francisco, California, USA, 2016, pp. 785–794.
[57] B. Müller, F. Bohn, G. Dreßler, J. Groeneveld, C. Klassert, R. Martin, M. Schlüter, J. Schulze, H. Weise, N. Schwarz, Describing human decisions in agent-based models – odd + d, an extension of the odd protocol, Environ. Model. Software 48 (2013) 37–48.
[58] M. McPherson, L. Smith-Lovin, J.M. Cook, Birds of a feather: homophily in social networks, Annu. Rev. Sociol. 27 (2001) 415–444.
[59] D. Roy, M. Lees, Understanding resilience in slums using an agent-based model, Comput. Environ. Urban Syst. 80 (2020) 101458.
[60] P. Windrum, G. Fagiolo, A. Moneta, Empirical validation of agent-based models: alternatives and prospects, J. Artif. Soc. Soc. Simulat. 10 (2007) 8.
[61] W. Glasser, Choice Theory: A New Psychology of Personal Freedom, HarperPerennial, New York, 1999.
[62] W. Alonso, Location and Landuse: toward a General Theory of Land Rent, Harvard University Press, 1964.
[63] S. Meikle, T. Ramasut, J. Walker, Sustainable urban livelihoods: concepts and implications for policy, in: DPU Working Paper, the Development Planning Unit University College London: London, 2001.
[64] K.J. Lancaster, A new approach to consumer theory, J. Polit. Econ. 74 (1966) 132–157.
[65] C. Shughrue, A model of nonlinear urbanization and information flows across India, Hixon Center for Urban Ecology 1 (2013) 1–19.
[66] M. Ben-Akiva, M. Bierlaire, Discrete choice methods and their applications to short term travel decisions, in: R.W. Hall (Ed.), Handbook of Transportation Science, Springer US, Boston, MA, 1999, pp. 5–33.
[67] J. Lu, Chapter 10 - interorganizational network dynamics in the wenchuan earthquake recovery, in: E.C. Jones, A.J. Faas (Eds.), Social Network Analysis of Disaster Response, Recovery, and Adaptation, Butterworth-Heinemann, 2017, pp. 143–159.
[68] R. Oldenburg, D. Brissett, The third place, Qual. Sociol. 5 (1982) 265–284.
[69] S. Bandyopadhyay, A. Rao, B. Sinha, Models for Social Networks with Statistical Applications, SAGE Publications.: Advanced Quantitative Technology in the Social Sciences, 2011.
[70] M.O. Jackson, T. Rodriguez-Barraquer, X. Tan, Social capital and social quilts: network patterns of favor exchange, Am. Econ. Rev. 102 (2012) 1857–1897.
[71] S. Wasserman, K. Faust, Social Network Analysis: Methods and Applications, Structural Analysis in the Social Sciences, Cambridge University Press, 1994.
[72] M.O. Jackson, B.W. Rogers, Meeting strangers and friends of friends: how random are social networks? Am. Econ. Rev. 97 (2007) 890–915.
[73] G. Chierchia, G. Coricelli, The impact of perceived similarity on tacit coordination: propensity for matching and aversion to decoupling choices, Front. Behav. Neurosci. 9 (2015).
[74] D. Centola, R. Willer, M. Macy, The emperor's dilemma: a computational model of self-enforcing norms, Am. J. Sociol. 110 (2005) 1009–1040.