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Toward near real-time flood loss estimation: post-disaster index

Annibale Vecere
PhD Candidate, School for Advanced Studies IUSS Pavia, Pavia, Italy

Mario Martina
Associate Professor, School for Advanced Studies IUSS Pavia, Pavia, Italy

Ricardo Monteiro
Assistant Professor, School for Advanced Studies IUSS Pavia, Pavia, Italy

Carmine Galasso
Associate Professor, Dept. of Civil, Environmental & Geomatic Engineering, Univ. College London, London, United Kingdom

ABSTRACT: The increase in the frequency and impact of extreme hydro-meteorological events worldwide highlights the need for more effective financial strategies providing coverage against the economic consequences of such events, particularly in developing countries. Near Real-Time Loss Estimation (NRTLE) models represent a new generation of catastrophe risk models that can serve as a basis for the development of innovative parametric insurance schemes. NRTLE models can help to estimate the impact of an extreme event, in near real time, for instance, through a Post-Disaster Index (PDI), upon which the issued payments depend. This study introduces a new methodology to compute such an index for flood events in the Philippines, which relies on satellite precipitation estimates, exposure information provided by national censuses issued by the Philippine Statistics Authority (PSA), and historic loss data from the EM-DAT International Disaster Loss database. Firstly, the risk model components (hazard, exposure and vulnerability) employed to generate the above index are described. Then, model performance in terms of number of affected residential buildings, estimated by means of the suggested PDI, is analyzed. Finally, an example of parametric insurance coverage based upon the designed PDI is illustrated.

Parametric or "trigger-based" insurance constitutes a new financial strategy devised to ensure enough financial resources before the occurrence of a catastrophic event. With this type of products, payouts are generally issued once a pre-defined threshold of an environmental variable (i.e., the trigger), highly correlated with losses, is exceeded. This study proposes the use of a Post-Disaster Index (PDI) as a trigger, linked to the development of the so-called Near Real-Time Loss Estimation (NRTLE) models, here applied to flood events.

NRTLE models represent effective tools for developing improved parametric insurance products where a hazardous event is first identified (in near-real time) and then an impact index, associated with the insurance payout, can be computed. The PDI is an index that can further improve the estimation of the impact and therefore reduce the uncertainty of the payout. These indexes, such the one proposed here, are designed to estimate the actual damage associated to an event with given characteristics and therefore to reduce basis risk, which emerges when there is a mismatch between modelled and actual losses.

NRTLE models belong to the category of the so called early or rapid loss estimation models aiming at providing an estimate of the loss or impact (e.g., affected population, casualties) in a given area, as a consequence of a considered natural hazard (such as floods or storms, as in this context), within few hours or days. These models can be classified in two main categories depending on the data used to assess losses:

1. Models using observations of effects (e.g., flooding) or impacts (direct and/or indirect losses) of the event on a given geographic area;
2. Models employing environmental variables (e.g. precipitation, wind, etc.) which cause (i.e. trigger) an extreme event.

The first type of models utilizes observations that are either directly or indirectly related to the impact of the event. Typically, these models rely on near real-time flood monitoring systems which have been widely developed in recent years (Lakshmi, 2017). Systems that utilize information provided by citizens (Fohringer, Dransch, Kreibich, & Schröter, 2015) through the web also belong to this first category. Recently, different communication technologies, such as social media, have also been tested with regards to their capabilities to complement disaster information in the aftermath of a major extreme event (Poser & Dransch, 2010).

The proposed NRTLE models belong to the second category of rapid loss estimation models above presented and a notable example, in this context, is represented by the models developed by the Caribbean Catastrophe Risk Insurance Facility Segregated Portfolio Company (CCRIF SPC) which offers parametric insurance against tropical cyclones, earthquakes and excess rainfall events on Caribbean governments (CCRIF SPC, 2015).

This paper proposes a newly-developed PDI for flood events to be included in a NRTLE model and presents its application to the Philippines, one of the most flood prone countries in the world. The proposed index is based on the use of a model to estimate losses and enables the calculation of the final payout of a parametric insurance coverage for hydro-meteorological events in the case-study country. Daily data from satellite precipitation estimates, exposure information from national censuses issued by the Philippine Statistics Authority (PSA), and loss data from the EM-DAT International Disaster Loss database are combined to develop the proposed PDI.

In the following, the procedure for the identification of flood events, the primary step in parametric insurance, is presented first and the risk model components (i.e. hazard, exposure and vulnerability) are described. The procedure for the calibration of a vulnerability function using data from the EM-DAT disaster loss database (Guha-Sapir, 2018) is then presented. Finally, the results provided by the devised index in terms of Occupied Housing Units (OHUs) affected by historical floods in the Philippines and the proposed parametric coverage are illustrated.

1. STUDY AREA

1.1. The Philippines' risk profile

The Philippines is an archipelago of 7,107 islands (1,000 of which are inhabitable) whose total area is approx. 300,000 Km^2. It is among the top global disaster hotspots worldwide and is exposed to a wide range of natural hazards. Located in the Pacific Ring of Fire, it is highly exposed to earthquakes, volcanic eruptions, and other geological hazards, as well as to multiple typhoons and monsoon rains causing several types of floods, which had a severe impact in the past (Figure 1). For instance, in the 2014 *Germanwatch Climate Risk Index*, the Philippines ranked 2nd worldwide among the most affected countries by disasters, with 85% of GDP in areas at risk.

Floods and windstorms (typhoons) have produced the highest economic damages in the country's history among all extreme event types (Table 1). The year 2013 was a devastating year for the country. A significant M7.2 earthquake and super Typhoon Yolanda (international codename: Haiyan) caused major damage and a significant increase in poverty levels in affected areas. In particular, Yolanda, a Category 5-equivalent typhoon with wind speeds over 300 km/h, struck the central Philippines, affecting an estimated 12.2 million people.

Table 1: Top 10 most damaging hydro-meteorological events in the Philippines, from EM-DAT (2018).

Philippines' top 10 hydro-meteorological events			
Disaster No	*Type*	*Date*	*Total damage ('000 US$)*
2013-0433	*Storm*	*08-11-2013*	*10,000,000*
2013-0274	*Flood*	*13-08-2013*	*2,190,000*
2015-0244	*Storm*	*12-07-2015*	*1,500,000*
2012-0500	*Storm*	*04-12-2012*	*898,352*
2014-0227	*Storm*	*15-07-2014*	*820,576*
1995-0209	*Flood*	*04-09-1995*	*700,300*
2009-0422	*Storm*	*29-09-2009*	*585,379*
1990-0122	*Storm*	*12-11-1990*	*388,500*
1990-0040	*Earthquake*	*16-07-1990*	*369,600*
2011-0379	*Storm*	*24-09-2011*	*344,173*

Nine of the country's 17 administrative regions were affected by the typhoon, covering 12,122 barangays (villages) in 44 provinces, 591 municipalities, and 57 cities. The typhoon caused over 6,200 reported fatalities and almost 1,800 people missing. In recognition of the high risk of the country due to natural hazards, the enactment of the Philippine Disaster Risk Reduction and Management (DRRM) Act in 2010 (Republic Act 10121) is enabling substantial progress in shifting the emphasis from emergency response to preparedness, mitigation and prevention.

2. MODEL COMPONENTS

As discussed above, the main aim of this study is to develop a PDI to provide an estimate of direct losses due to hydro-meteorological events in the Philippines. This index can serve as a basis for the computation of the parametric coverage payout, which will be described in Section 2.2. Consistently with conventional risk models, three main components, namely hazard, exposure, and vulnerability, are used to compute the PDI and will be investigated in the following sub-sections.

2.1. Hazard

The hazard component consists of a procedure for the identification of hydro-meteorological events over the Philippines based on the daily precipitation derived from the CMORPH (CPC MORPHing technique) satellite precipitation estimates (SPEs).

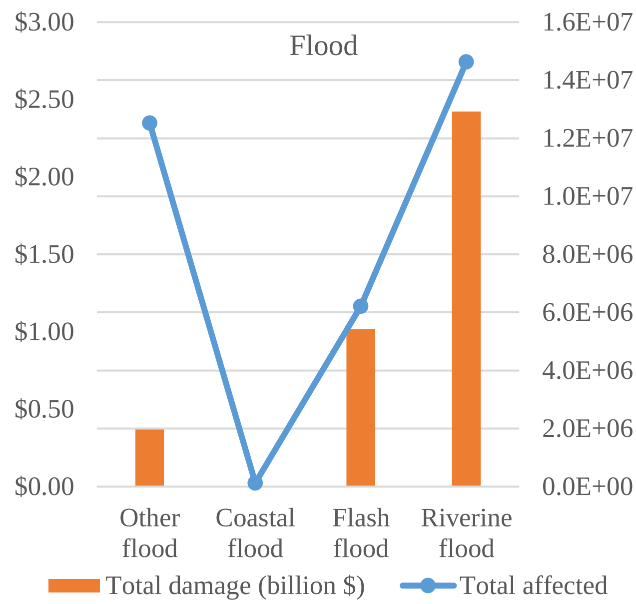

Figure 1: Total damage and total population affected due to different types of floods in the Philippines, from EM-DAT (2018).

This dataset was selected as it satisfies the requirements for a trigger to be used in NRTLE models for floods: low latency (18 hours), at least 20 years of temporal coverage (from 1998 to July 2017), suitable temporal (30 minutes) and spatial (approximately 8 km) resolution.

The procedure for the identification of flood events in the Philippines can be summarized in four main steps and is thoroughly described in (Vecere, Martina, Monteiro, & Galasso, 2019):

1. Computation of the number of cells with precipitation above a given threshold (Thr.) - Thr.1 - (active cells), over the Philippines;
2. Definition of days in which the number of active cells exceeds a given percentage of the country's cells - Thr.2 - (active days) within the investigated period;
3. Definition of event start and end dates;

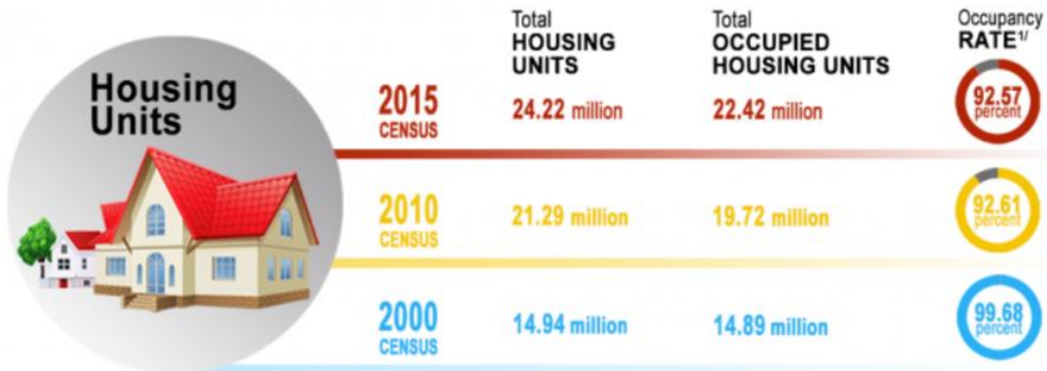

Figure 2: 2015 Census of Philippines' Population: Housing Units and Occupied Housing Units from [PSA, 2018].

4. Identification of events within a control period (i.e. 3 days).

As a result of the event identification process, almost 170 hydro-meteorological events were detected in the period 1998 – July 2017. Subsequently, for each event, the highest precipitation value above Thr.1 (in accordance with event definition procedure) on every country's affected cell between the start and end date was used as hazard variable.

2.2. Exposure

Exposure information was collected using official housing data by city/municipality, which the Philippines Statistics Authority makes publicly available (Philippines Statistics Authority (PSA), 2018). Housing characteristics in the Philippines were collected in the context of the 2015 national census of population. The 2015 national census provides several types of housing information, either related to previous censuses or specific for the 2015 census: number of OHUs for censuses from 1960 to 2015, number of households, ratio of household and household population to OHUs by type of building, etc. In addition, also information on construction material of outer walls and roof, occupancy types (e.g., single house, multi-units residential, duplex house, etc.) and tenure status is provided. The collected data reveals a higher absolute number of housing units but lower occupancy rate with respect to the previous censuses (Figure 2). Interestingly, around 80% of the total OHUs is classified as single house, in contrast with western countries (e.g., Europe) where the majority of residential buildings can be classified as multi-unit residential type.

For the present study, the number of OHUs from the censuses overlapping the period covered by the CMORPH dataset (i.e., from 1998 to 2017) were used. Specifically, the 2000, 2007, 2010, 2015 housing data was employed to calibrate the vulnerability functions with respect to historical data, as it will be presented in the next sub-section.

Data on OHUs from censuses was first linked to a shapefile of the Philippines' municipalities (downloaded from the National Mapping and Resource Information Authority (NAMRIA) of the republic of the Philippines (OCHA Philippines, 2018)). Then, the resulting shapefiles were converted to a raster matching CMORPH resolution (Figure 3) through a code developed in the R programming language (R version 3.5.1 and RStudio 1.1.453).

2.3. Vulnerability

The proposed vulnerability curve envisages a link between the daily precipitation and the percentage of affected OHUs as a result of a flood event. To this end, a generalized beta distribution with parameters α and β was utilized (Figure 4). The number of affected OHUs on every cell is computed using daily precipitation as independent variable (Figure 4). An upper limit of 75% for the

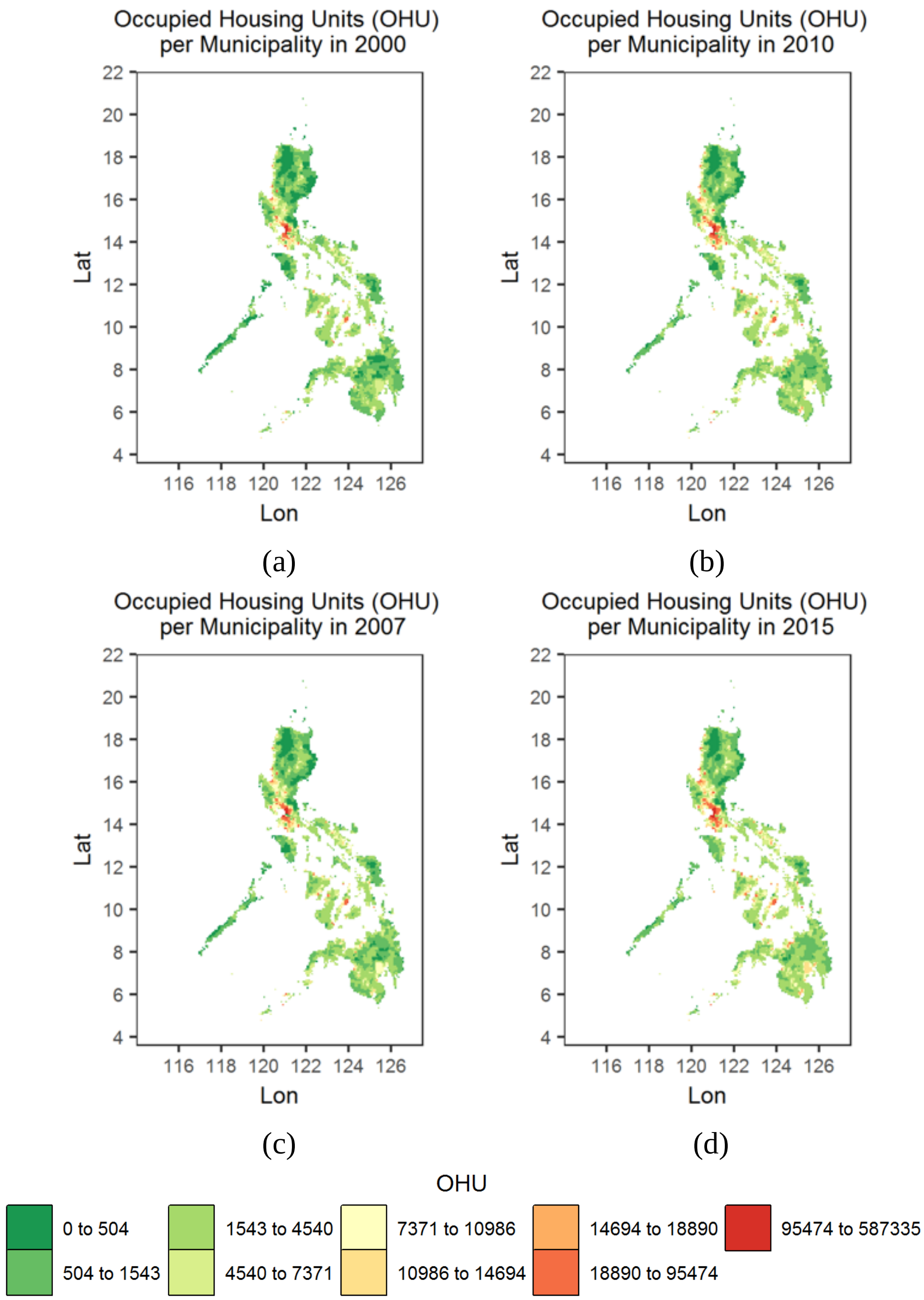

Figure 3: Rasterized OHU with CMORPH's resolution from Philippines's Statistics Authority's 2000 (a), 2007 (b), 2010 (c), 2015 (d) censuses.

estimated affected OHUs ratio was assumed, considering that, even for extremely high daily precipitation values, it is unlikely that a higher percentage of buildings is hit by a flood on each cell, because of the presence of buildings which are less vulnerable or not damaged by floods thanks to their characteristics (e.g. high buildings) or location (e.g. on top of hills). In order to calibrate the vulnerability curve, the procedure was repeated for 100 different combinations of the coefficients α and β by recursively assuming a value between 1 and 10 for each of them. The criterion adopted to identify the best configuration of the vulnerability curve was to evaluate the R^2

coefficient of a series of two arrays, the modelled affected OHUs and the affected buildings from EM-DAT (historical data). The first array was represented by the affected OHUs at the national level (i.e. resulting by the sum of affected OHUs on every cell where at least 65mm/day fell, based on CMORPH SPEs), computed for every historical event detected through the methodology for flood event identification described above. A hundred different arrays of modelled affected OHUs were produced, one for each combination of α and β coefficients. Each of these arrays was assessed (by means of the R^2 coefficient) with respect to the one of the affected buildings, computed by using EM-DAT displaced population reported in correspondence of the detected events, through an assumption on the average family.

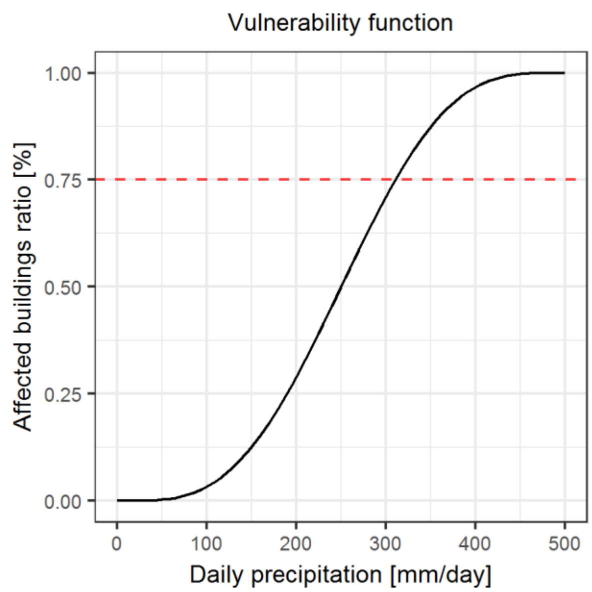

Figure 4: Vulnerability function relating affected OHUs and daily precipitation (generalized beta distribution α=3 and β=2).

EM-DAT contains two different types of impact measures for flood and storms in the Philippines (Guha-Sapir, 2018): total estimated damage and total population affected. The number of affected people is a good indicator to calibrate the above vulnerability function, linking the precipitation (i.e. SPEs) and the physical damage on residential buildings. Furthermore, EM-DAT follows the recommendations of the UNDP country classification, according to which the average size of a family in developing countries is equal to five, therefore, the number of EM-DAT affected buildings was computed by dividing the number of total affected people by five.

Only events featuring non-zero values and a reported displaced population lower than their average plus two times the standard deviation were used here (i.e. to exclude outliers). The vulnerability function with α and β equal to 4 was the one that produced the best agreement with respect to EM-DAT.

3. RESULTS AND DISCUSSION

3.1. PDI computation

Flood impact estimation was performed using the described approach and considering OHUs from the 2015 census exclusively. In this way, the impact of historical events was estimated by assuming the current exposure ("as if" analysis). The comparison between modelled and historical affected OHUs, shows that, in general - more specifically up to the 90th percentile of the two distributions - the proposed model tends to overestimate the number of affected housing units with respect to the same data derived from EM-DAT affected population. This is probably due to the higher number of exposed assets of the 2015 census with a registered increase above 50% with respect to the 2000 census, for example. On the other hand, the underestimated results for catastrophic events (above the 90th percentile) indicate that the proposed model is not able to capture some factors that exacerbate the physical impact of hydro-meteorological events, such as wind-induced damage, for instance, in the case of storms. The relative error between the two distributions of modelled and historical OHUs values was equal to 13.7%.

3.2. Parametric coverage

As model presented above is designed to be linked to a parametric insurance policy. In the present study, the payout is directly associated to a PDI estimate, which is intended to better reproduce the physical damage (i.e., direct economic losses). Typically, in parametric insurance, the relationship between the payout and the observed environmental variable is named payout curve.

This function, which, in this case, relates the number of affected OHUs (i.e. the PDI) with the insurance payout, is linear: the so-called attachment (i.e. PDI value after which a payout is issued, 35,000) and exhaustion (PDI value corresponding to the coverage limit, that is maximum amount that can be paid out under a policy, 14 M) points and the coverage limit ($ 20M) define the proposed parametric contract. Attachment and exhaustion points were determined according to financial criteria (i.e. level of damage that can be retained by the insured party and an acceptable ratio between premium and coverage limit, as discussed below) and to optimize the number of detected events with an associated non-zero payout. The coverage limit was arbitrarily set to $20,000,000 per year, a level comparable to the one used to for similar policies (ASEAN, GFDRR, & UNISDR, 2012; CCRIF SPC, 2016). In this case, the mean annual payout was approximately $1,950,000 corresponding to less than 10% of the coverage limit (Figure 5).

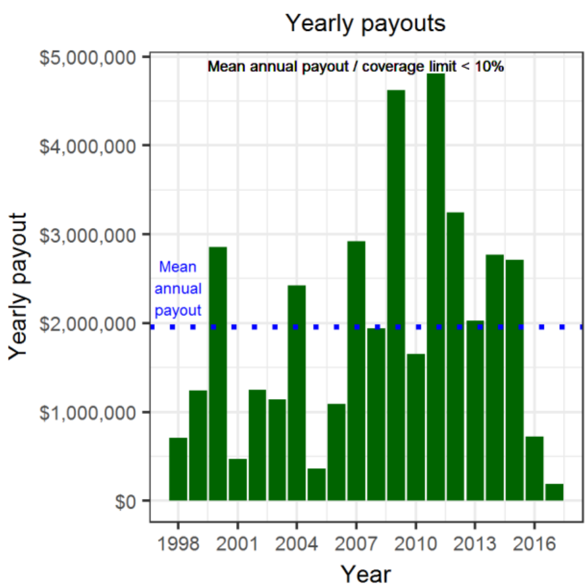

Figure 5: Yearly payout and mean annual payout.

Premiums are typically computed as the average annual payout plus the insurer profit and their ratio with respect to the bond principal (i.e. bond financial capital), which can be greater than or equal to the yearly coverage limit, typically ranges between 3% and 10% (Cummins, 2008). Such relationship between the average payout (premium) and coverage limit is justified by the cost efficiency of the proposed cat bond for both the reinsurance party, which is generally interested in offering a profitable and financially sustainable product, and the insured country, which looks for an advantageous coverage at a reasonable price.

4. CONCLUSIONS

This paper presents a PDI providing a near real-time estimate of the OHUs affected by hydro-meteorological events in the Philippines. The model makes use of CMORPH SPEs, a product freely available with a global coverage. An ad hoc developed methodology to capture hydro-meteorological events in the Philippines based on CMORPH daily precipitation estimates was used as input hazard. Occupied housing data from the country's national censuses was employed to model the exposure. A generalized beta distribution with α and β coefficients calibrated with respect to EM-DAT affected population data (conveniently translated as affected OHUs) was developed and adopted as vulnerability function to compute the PDI here proposed. Future developments of the work could envisage the use of detailed building information (e.g., presence of basement, number of floors, etc.) or even the inclusion of a secondary trigger, such as wind speed, which is another cause of direct damages in the case of storms. Even if the proposed impact index seemed to overestimate the historical event impacts, as consequence of the larger exposure resulting from the 2015 census, (and to underestimate the catastrophic ones) the suggested PDI proved to be a promising index for the development of a cost-effective parametric coverage for hydro-meteorological events in the Philippines for both parties involved in an insurance contract. This is illustrated in terms of reported average annual payout and its ratio with respect to the policy coverage limit (below 10%).

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