# Toward near real-time flood loss estimation: model structure and event definition

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ABSTRACT: Near Real-Time Loss Estimation Models (NRTLEMs) represent effective tools for developing improved parametric insurance products. This type of financial instruments enables rapid payments as they use one or more environmental variables measured immediately after the event and defined as trigger(s), to identify disaster events and predict the consequent impact. This study presents the preliminary development of such a NRTLEM, specific for floods. Given the importance of the event identification within the proposed methodology, different types of triggers are investigated and compared, with special focus on satellite precipitations estimates. NRTLE-based framework for identification of flood events in the Philippines using satellite precipitation estimates is investigated here. The methodology for event identification and the model calibration procedure are discussed. Finally, the model performance is investigated and the optimal configuration of model parameters minimizing basis risk, i.e., the mismatch between insurance claim settlement and the actual losses, is presented for the case-study application.

## 1. INTRODUCTION

According to the 2016 World Disasters Report by the International Federation of Red Cross, in the last decade, natural hazards have affected more than 1.9Bn people, killed 700k and caused $1.9Tr worth of damage [IFRC, 2016]. These figures are expected to worsen in the near future due to both population increase (and consequent increase of the exposed assets) and the potential significant impact of climate change. The expected increase in the overall cost of natural hazards highlights the importance of efficient financial strategies to improve preparedness and enable rapid response and recovery after a disaster occurs. In particular, there is a need to develop ex-ante funding mechanisms that are more efficient in meeting post-disaster needs and fostering disaster risk management (DRM) efforts [Cummins & Mahul, 2009]. In recent years, innovative financial instruments have been developed to ensure financial resources before the occurrence of an event. Among these, increasing attention is being paid to the use of parametric or 'trigger-based' (or index-based) insurance, especially in countries with low financial capacity. Parametric insurance enables rapid action/payments and is cost-effective, when compared to traditional (indemnity-based) insurance. In the case of parametric insurance, payments are made on the basis of the exceedance of weather-related or geological observations, also defined as triggers, such as the cumulated (or average) rainfall over a given period, maximum wind speed or the magnitude of an earthquake [Ibarra, 2012]. The payout can be either fixed (related to the occurrence of a predefined event) or can be linked to an *ad-hoc* developed index computed by means of the above-mentioned parameter. Traditionally, the monetary coverage provided by parametric insurance products is aimed at covering short-term revenue shortfall and filling the most pressing needs between short-term disaster relief and long-term redevelopment aid. Parametric insurance is inherently subjected to potential mismatch between claims settlement and the actual losses suffered by the insured and, more generally, to the risk that the payout does not correspond to the occurrence of an actual event. This type of risk is generally referred to as basis risk [Albertini & Barrieu, 2009].

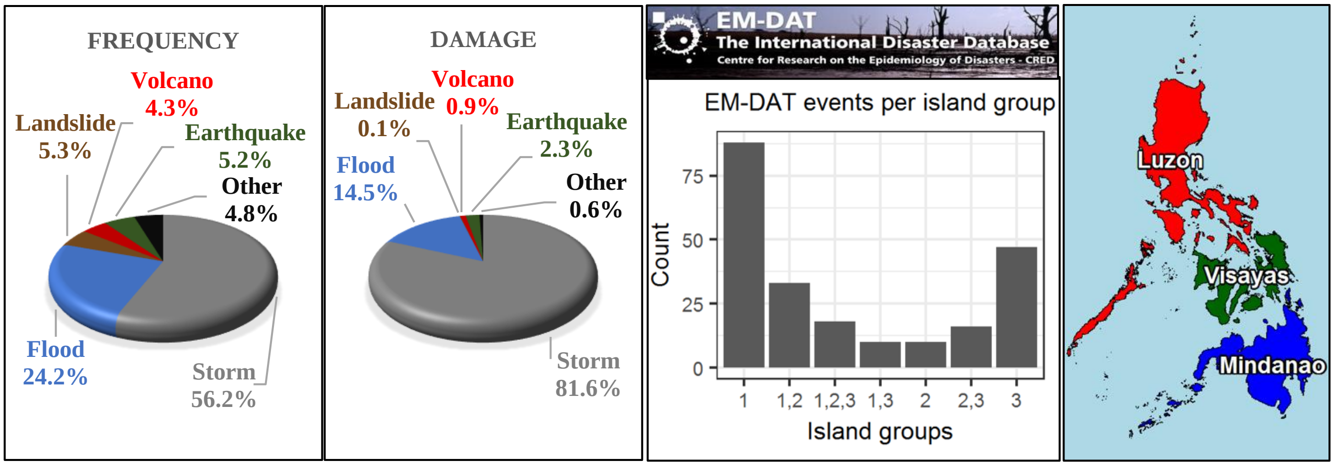
This study presents the first step toward the development of a Near Real-Time Loss Estimation (NRTLE) model, here applied to flood events, to be implemented in a new generation of parametric insurance products. When compared to conventional catastrophe risk models, NRTLE models bring the time component into play and they are intended to first identify the occurrence of an event, and then produce a loss estimate immediately after (in near real-time) the event has been declared. In particular, this paper describes the methodology to identify triggering events, which is a crucial aspect in any NRTLE model.

The main added value of NRTLE models is represented by the use of the same input data and structure for both risk assessment, i.e., the pricing phase, and the estimation of losses in near real-time. This represents a fundamental difference with respect not only to traditional risk assessment models, but especially regarding other available post-disaster impact methodologies (PAGER, GDACS, etc.) [Mehta, 2017; Wald et al., 2010]. NRTLE models are designed to be consistent with traditional risk assessment models in terms of both hazard and estimated losses. Additional requirements are represented by the accessibility in near real-time of the selected trigger, which also needs to be highly reliable (in terms of accuracy of measurement of the environmental variable). Finally, the trigger must be highly correlated with losses (i.e., efficient). An application of the proposed NRTLE-based framework for flood events in the Philippines, one of the most flood prone countries in the world, is presented. Firstly, following the description of a reference historic disaster loss dataset, the selected environmental variable (satellite precipitation estimates) is analyzed and the features that make it a suitable trigger for flood NRTLE are described. Then, the procedures for event identification and model calibration are described. Finally, the model performance is assessed and the configuration for optimal thresholds, i.e. the one that minimizes the basis risk for the specific case-study region, is presented.

## 2. STUDY AREA AND INPUT DATA

### *2.1. 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 and is exposed to a wide range of natural and human-induced hazards (Figure 1a), which is a limiting factor to its sustainable development. 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. 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. In recognition of the country's vulnerability to natural disasters, 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. Significant resources have been provided for ex-ante investments and new areas of engagement have been considered in the policy dialogue.




*(a)* *(b)* *(c)*

*Figure 1: The Philippines' disaster events (a) frequency, (b) damage and (c) reclassification of hydro-meteorological events by island group between 1998 and July 2017, from EM-DAT (2018).*

However, challenges remain in enabling implementation of disaster risk reduction investments in several priority sectors.

*2.2. Historical event data: the EM-DAT database*

The event information used for the present study was collected from the EM-DAT database [Guha-Sapir, 2018], which is a global database containing information related to the occurrence and consequences of more than 21,000 disasters worldwide from the beginning of the 20th century onwards. EM-DAT provides the specification of disaster type (e.g. storm, flood), disaster subtype (e.g. tropical cyclone, pluvial flood) and in some cases also an estimate of the magnitude of the event in terms of $Km^2$ (flood) or Kph (storm) and (or) Latitude-Longitude coordinates of the event location. In terms of measured impact, total deaths, total affected (i.e. number of individuals affected, injured and homeless) and total damage (physical damages/direct and indirect economic losses) are the variables included in the EM-DAT database. Specifically, detailed data on historical hydro-meteorological events in the Philippines is used as an historical catalogue in this study for model calibration and validation purposes. The original data (493 events) was pre-processed to filter only events from January 1998 and July 2017, for consistency with available precipitation data (as discussed in the next sub-section). As a result of this process, a total of 222 disasters were obtained. In order to allow for an assessment of the location accuracy of the events simulated by the proposed NRTLE model, a reclassification of the EM-DAT events based on the three main Philippines' island groups - Luzon, Visayas, Mindanao - has been carried out (Figure 1c).

*2.3. Trigger: CMORPH precipitation estimates*

The proposed methodology for the near real-time identification of hydro-meteorological events (i.e. floods and storms) in the Philippines is based on a single trigger, that is the daily precipitation. In the present study, the CMORPH (CPC MORPHing technique) precipitation estimates are the selected input. CMORPH produces precipitation estimates in the latitude band 60°S – 60°N with high temporal (30 minutes) and spatial (approximately 8km at the equator) resolution. Temporal coverage is from 1998 to present. Its latency is quite low, since CMORPH estimates are available after 18 hours from acquisition. The technique used to produce precipitation estimates uses exclusively low-orbiter satellite microwave observations, which are transported using spatial propagation obtained entirely from geostationary satellite InfraRed (IR) data. This procedure is aimed at determining precipitation features in half hourly periods between microwave scans and is

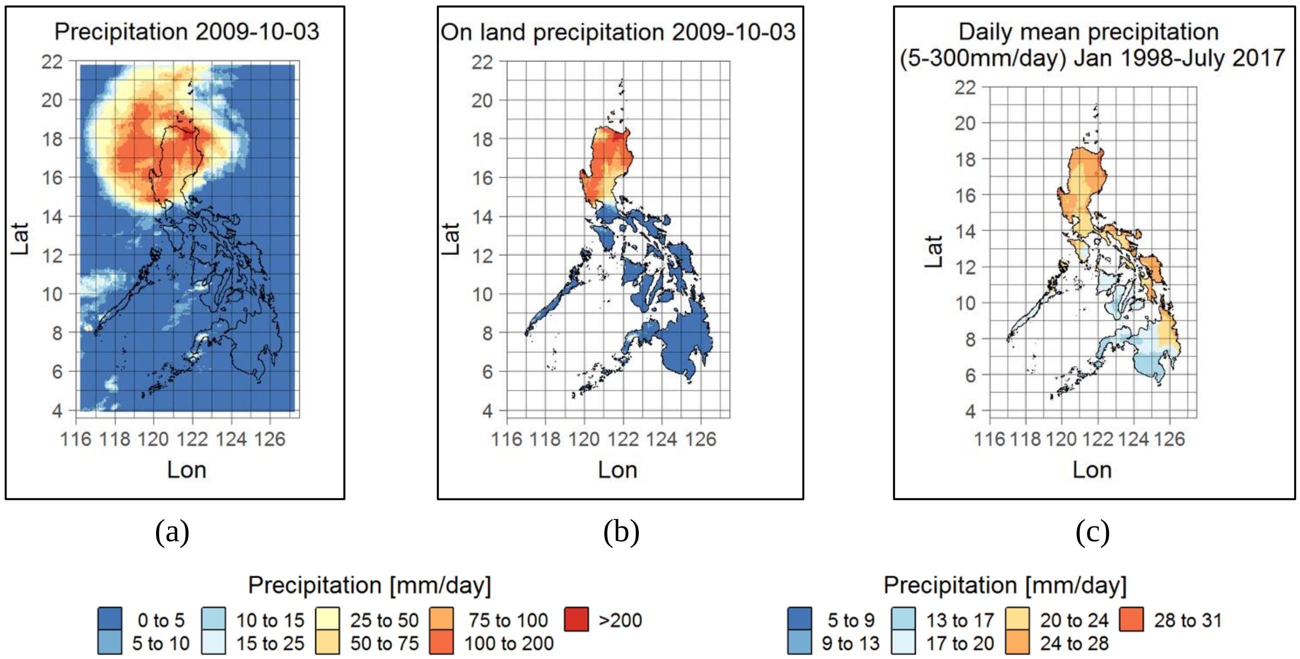



*Figure 2: CMORPH precipitation over the Philippines on 2009-10-03. Precipitation over an area with a 50 km buffer from country boundaries (a) and precipitation on land (b). Daily mean precipitation values between 1998-01 and 2017-07 (c).*

referred to as "morphing" technique [Joyce et al., 2004]. CMORPH data was processed through a code developed in R programming language (R version 3.5.1 and RStudio 1.1.453) to compute daily totals of precipitation from the original half-hourly data. Original data was first filtered over a rectangular area around the Philippines (Figure 2a). Subsequently, daily precipitation values were computed and finally they were masked over the country borders (Figure 2b). The resulting raster was composed of 4,630 cells with a resolution of approximately 8 km by 8 km. A daily mean precipitation map (values between 5 and 300 mm/day) was also produced to obtain a visual representation of the areas most affected by higher daily precipitation values (Figure 2c).

It is worth noting that 25% of the daily precipitation values are lower than 1 mm/day, a low value caused by the length of the investigated period. The 75$^{th}$ percentile is 12.1 mm/day and 99% of daily precipitation values are lower than 86 mm/day.

## 3. METHODOLOGY

### *3.1. Event definition procedure*

The proposed procedure for the identification of hydro-meteorological events in the Philippines, based on the daily precipitation, can be summarized in four main steps:

1. Computation of active cells over the area of interest (the Philippines);
2. Definition of active days within the investigated period;
3. Definition of event start and end dates;
4. Identification of events within a control period.

The first step (1) is represented by the identification of the active cells, defined as those cells where a predefined precipitation threshold is exceeded. Such a precipitation threshold is defined as Threshold 1 (Thr.1) (Figure 3). The next step (2) is the computation over the whole Philippines of the total number of active cells for each given day (Figure 4).

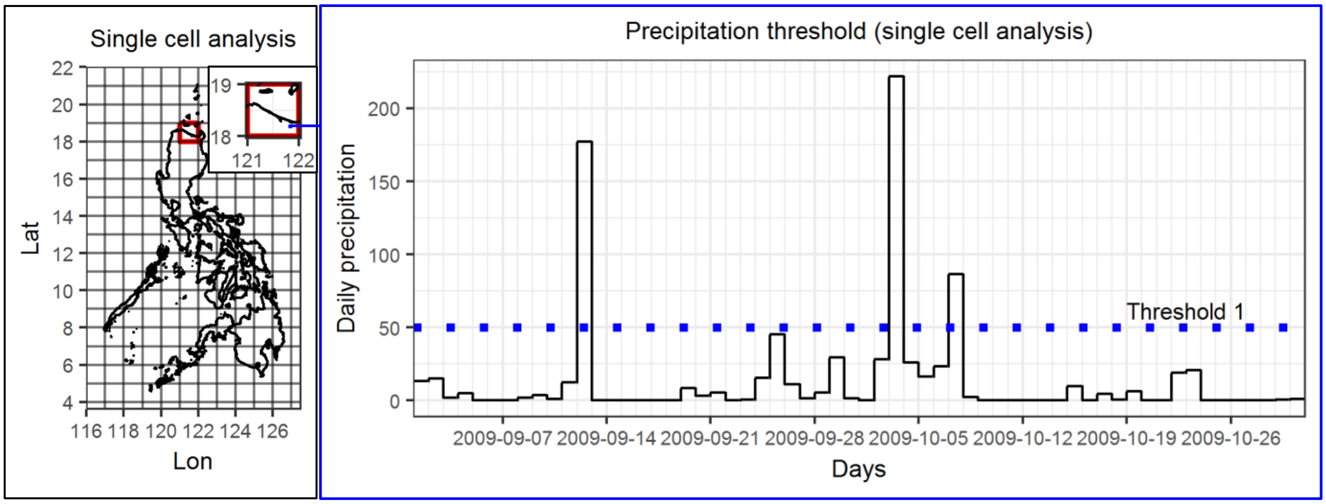



*Figure 3: Computation of active cells over the Philippines.*

The event duration [step (3)] is estimated on the basis of this binary array of active days. The start date of the event is set on the first day in which the number of active cells is above a number of cells (or cell percentage) threshold, Threshold 2 (Thr.2), and the end date of the event corresponds to the day in which the number of active cells drops below the threshold with a period of tolerance (here set to one day).

Figure 5 contains a graphical representation of the event definition above described. The last step of the procedure (4) is represented by the definition of a control period, in which to assess if an event has occurred. Two main reasons justify the adoption of a period longer than one day to check estimated events with respect to the historical (real) ones. Firstly, daily analysis would be misleading (events usually last more than one day) and demanding. The same can be said for its opposite, that is an event-based approach. Secondly, the so-called "72 hours clause" is typically applied to perils such as storm or flood in the insurance and reinsurance sector for the parametric products associated with this kind of models. Hence, an aggregation over a period of three day was here selected (Figure 6). Therefore, a final binary array was produced based on the presence of at least one day with a number of active cells above the active cell threshold (Thr.2)

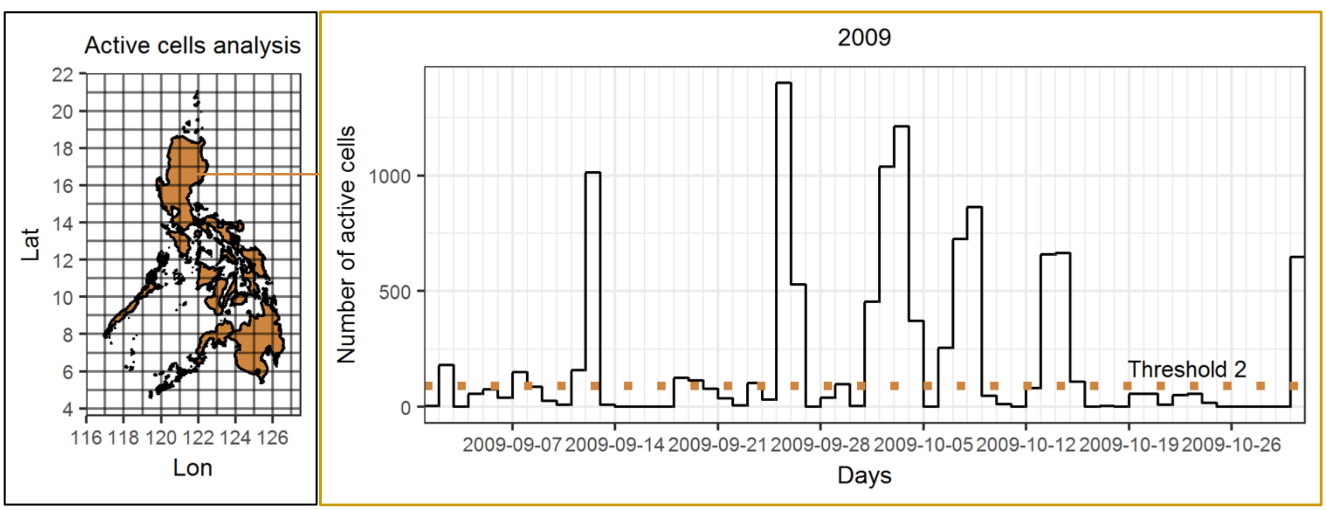



*Figure 4: Computation of total number of active cells for each day*

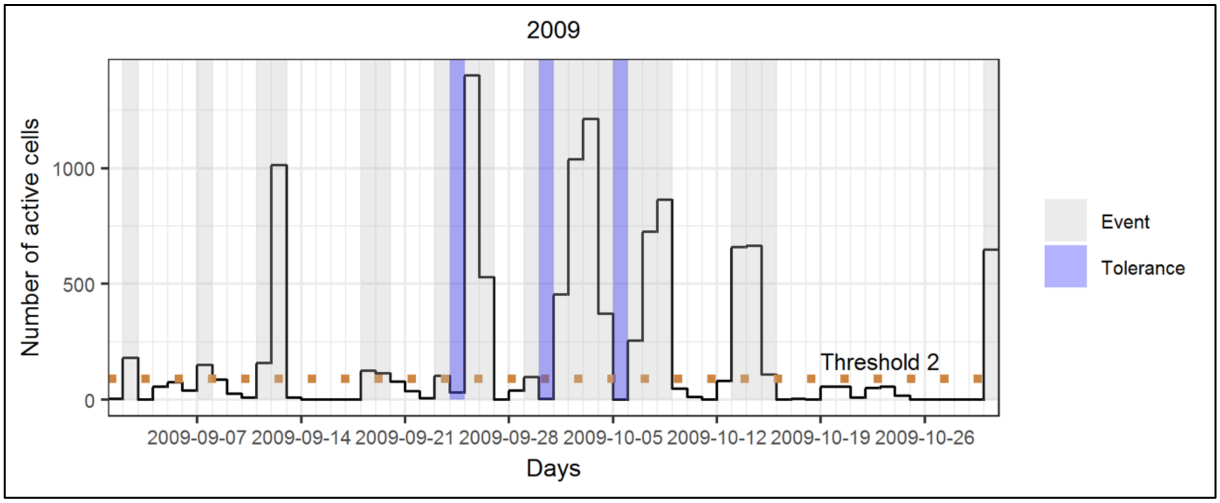



*Figure 5: Event definition with highlighted period of tolerance.*

within the 3-day control period above discussed.

*3.2. Model calibration and performance metrics*

The model calibration was aimed at identifying the optimal values for Thr.1 and Thr.2 and was conducted using two sets of values for both of them.

Each of these thresholds is used to produce the binary vector above described that has to be verified against an analogous binary array produced for historical (real) events. This array is created from the EM-DAT events and assuming the same control period reported earlier (3 days). The use of binary arrays to verify a forecast against a corresponding measured observation is derived from the weather forecast verification sector [Stanski et al., 1989]. Typically, a contingency table is created to conduct a forecast verification. The 'hits' represent the number of events which occurred and were detected by the model. 'Misses' refer to the number of events which occurred and were not detected by the model. The 'False alarms' entry is the number of events which did not occur but were detected by the model. 'Correct negatives' refer to the number of events which did not occur and were not detected by the model. Two useful metrics to investigate the model performance are the Probability of Detection (POD) and the Probability of false detection (POFD) which can be obtained using, respectively, Eq. (1) and (2):

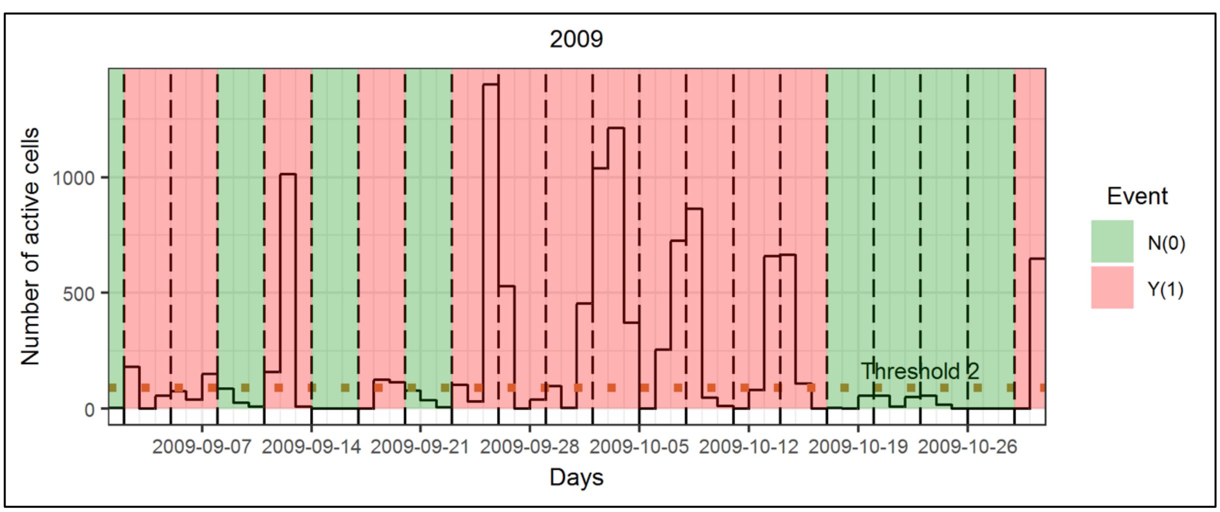



*Figure 6: Event definition with highlighted period of tolerance.*

*Table 1: Contingency table.*

| | ***Real events*** | |
|---|---|---|
| ***Modelled events*** | *Yes* | *No* |
| *Yes* | *Hits* | *False Alarms* |
| *No* | *Misses* | *Correct Negatives* |

The POD measures the fraction of the observed "yes" events which are correctly detected by the model. Conversely, the POFD calculates the portion of the observed "no" events which were incorrectly identified as "yes" event from the model.

$$POD = \frac{Hits}{Hits+Misses} \tag{1}$$

$$POFD = \frac{False\ alarms}{False\ alarms+Correct\ Negatives} \tag{2}$$

To provide an overall measure of the model performance, a Skill Score (SS) metric can be defined as the difference between the two above reported statistics, according to Eq. (3):

$$SS = POD\text{-}POFD \tag{3}$$

Two sets of threshold values (i.e., 1, 2.5 and from 5 to 100mm, with 5mm steps for Thr.1 and from 1% to 15%, with 0.5% steps for Thr.2). have been used for a total of 638 runs. Another analysis tool that is commonly used to assess the accuracy of a continuous measurement for predicting a binary outcome is the so-called relative operating characteristic (ROC). The ROC curve shows the POD on the vertical axis against the POFD on the horizontal axis for different combinations of Thr.1 and Thr.2. Model calibration (training) was accomplished by filtering recursively 18 years; the model was then tested on the remaining 2 (testing), that is through a bootstrapping method. For each training period, all 638 different model configurations were run.

## 4. RESULTS: PERFORMANCE METRICS AND BEST MODEL CONFIGURATION

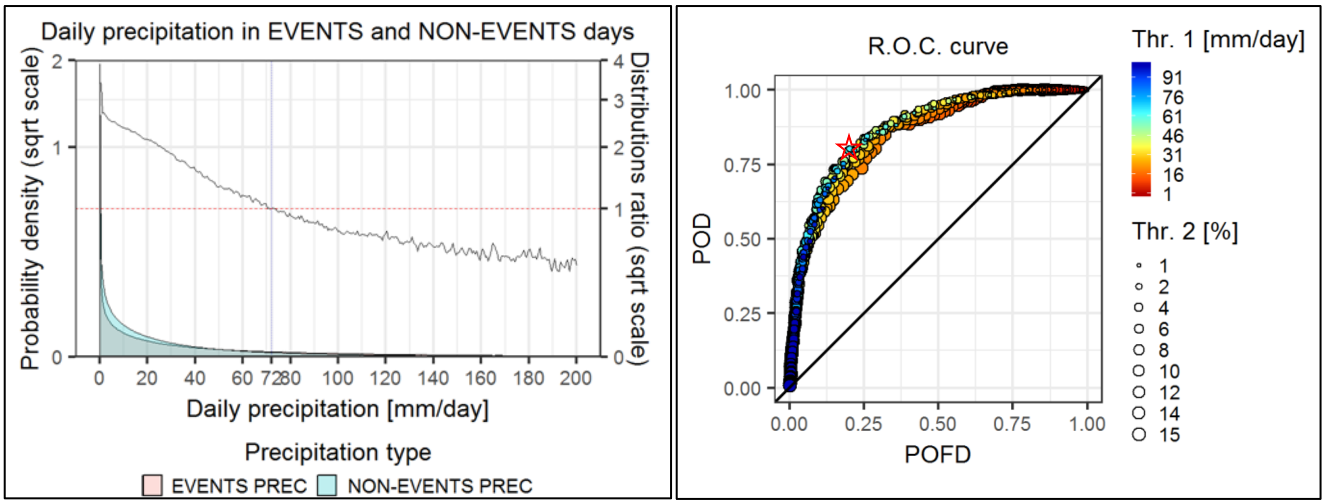
The best model configuration for almost all investigated training periods (except period 1998-2015) was found to be Thr.1 = 65mm/day and Thr.2 = 2%. Model performance was finally assessed over the whole investigated period (1998-2017) by using the 638 different combinations of Thr.1 and Thr.2. This analysis confirmed the best model configuration reported above. The conditional distributions of precipitation on real-event days and on non-event days was also compared to assess if the rainfall is a reasonable predictor for a flood event. Figure 7a clearly shows that for low daily precipitation values, the non-event curve stays above the event one, indicating that, during non-event days, the daily precipitation is generally lower than the one in event days, as expected. This trend is reversed after 72mm/day, as it is clearly visible by the value of the distribution ratio which becomes lower than one after that level.

This suggests that high daily rainfall values are correlated with flood events and therefore with their losses. The ROC curve (Figure 7b) confirms the optimum model configuration (Thr.1 = 65 mm/day and Thr.2 = 2%, highlighted by a red star), which typically coincides with the farthest point from the diagonal line. Indeed, this point represents the model with the best performance with respect to a completely random model (diagonal line). The event location accuracy of the model was also assessed and, although it is not included here due to space limitations, promising results were obtained.

## 5. CONCLUSIONS

This study introduced the first component of a NRTLE model, specifically applied to flood risk due to hydro-meteorological events in the Philippines. The model relies on CMORPH satellite precipitation estimates as a trigger to identify a disaster event. Model performance was assessed using methodologies available in the literature for forecast precipitation verification and the model calibration was performed using a bootstrapping method to train recursively the model on 18 years and test it on the remaining.

The best model configuration resulted for a precipitation threshold value, Thr. 1 = 65mm/day, and a number of active cells threshold, Thr. 2 = 2%. The R.O.C. curve, which was produced by running the model using all 638 different combinations over the whole period of analysis, confirmed an overall good model performance and the best model configuration thresholds obtained in the calibration phase.




(a) (b)

*Figure 7: Conditional distribution of (a) CMORPH precipitation below 200mm/day and (b) ROC curve.*

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