# DISASTER INSURANCE: NEW PARAMETRIC CONTRACTS BASED ON SATELLITE IMAGES

**Eric Bouyé, Jean-Xavier Bourre & Joey Hyun Joon Lee***
The World Bank
1225 Connecticut Ave. NW
Washington DC 20433, USA
{ebouye,jxbourre,hlee10}@worldbank.org

## ABSTRACT

Parametric insurance consists in a contract where the buyer enters into a protection that will payout under predefined conditions, comparing the value of a parameter or an index to a trigger. It allows to be protected against most of natural catastrophic events (e.g. flood, fire, hurricane, earthquake). The main advantage of parametric insurance is the guarantee of a timely, diligent and transparent process to release needed funds after the catastrophe, particularly critical for developing countries. Convolutional Neural Networks (ConvNets) on satellite images can be used to build indicators of disasters, for example by comparing images before and quickly after an event. Our project explores a set of disaster indicators (some including the a monetary component to the indices), and their backtesting for historical disasters. The objective is to promote a new set of ConvNets based insurance instruments and their underlying pricing methodology. We would like to emphasize the importance of transparency - that includes code publishing -, stability and robustness of the ConvNets.

## 1 PROBLEM

In traditional disaster risk insurance, a premium is paid by a cedent to an insurer to cover for the actual loss incured during an incident or a specific type of peril (e.g. hurricane, flood, earthquake, fire). Payments are made after an investigation and an assessment of the actual loss. This process can be lengthy and does not often meet the urgent needs from the impacted countries, especially in developing countries where the population is often the most fragile. To mitigate this drawback of traditional insurance contracts, parametric (or index based) insurance has emerged. It covers the risk of a predefined event (for which a probability is estimated).
According to an analysis of disaster risk insurance market - see the Deal Directory from artemis.bm -, the main types of payout by order of importance on the Insurance Linked Securities (ILS) market are indemnity (based on actual losses), industry loss triggers (estimates of industry losses by a third-party entity), and parametric insurance. The main advantage of parametric insurance is that it allows a diligent and transparent claim process with a low chance of dispute. However a drawback of the parametric approach is the basis risk, that occurs in case of discrepancy between the actual losses and the triggered payment. A source of basis risk could be a change in one of the underlying parameter of the contract. For example, in a parametric insurance sold by the African Risk Capacity to Malawi in 2015, the trigger was designed around a reliable rainfall model, but the payout was calibrated using propritary model of hydric stress on specific types of crops. In reality, farmers switched to a different crop than the model (with 90 day-growing period versus 120-140 days) that happened to be very affected by this season rain pattern. As a consequence, despite severe loss of crops and resulting humanitarian crisis in certain areas, no payment was done after the 2015-2016 season drought. The situation led to political troubles, and the model had to adjusted to trigger a payout (1). Basis risk can also originate from model risk. An excess rainfall with flooding in Jamaica in

*The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

2017 did not trigger a \$200mion threshold embeded in a parametric contract sold by the Caribbean Catastrophe Risk Insurance Facility (CCRIF) because the modeled loss was only \$100mion (for a \$400mion estimated actual loss) (2). Another example is the FONDEN 2017 multi-peril cat bond that was issued in 2017. The September 7th 2017 Chiapas earthquake triggered the payout of the cat bond, while the September 19th Mexico earthquake, that had a much bigger impact (in term of infrastructures and lost lives) would not have triggered payments.

## 2 PROPOSAL

The objective is to build an index which has a high correlation with the actual financial loss incured in case of disaster. Convolutional Neural Networks on satellite images can be used to build indexes for disasters, by comparing images before and after the event. As this index is as close as it could be from the actual damages, it reduces the basis risk. We want to backtest a set of indicators for 3-5 countries by comparing satellite images pre and post-disaster.
In practice, ConvNets can be used for segmentation (loss/no loss) to detect destroyed buildings and infrastructures, by comparing the satellite images before and after an event. The granular information is aggregated into a Disaster Level Index that allows to precisely assess the degree of destruction for a specific zone. The payout is proportional to the aggregated level of destruction. The Disaster Level Index (DLI) is defined as follows:

$$\mathrm{DLI} = \sum_{i \in A} w_i f_i$$

with $i$ the index for a specific building, a specific block or arbitrary area (e.g. acre, pixel area), $w_i$ the weight affected to area $i$ (actual value or estimated exposure), and $f_i$ the indicator function that indicates if the segmentation algorithm has detected any destruction in the area.

Morover, an index needs to meet a set of requirements. An example of best practices are for example provided by the European Securities and Markets Authority (ESMA, 2013) (4), and could be applied to indexes obtained through the use of convolutional neural networks for the identification of losses.

1. Methodology: The methodologies for the calculation of the disaster index should be documented and be subject to regular control to verify its reliability. In practice, the algorithm used should be provided, including the set of hyperparameters (e.g. network structure, number of layers, dimension of each layer, penalty functions, regularization parameters). The index should be sufficiently robust to changes that are not of direct interest for measurement (e.g. weather conditions).
2. Governance structure: The process for setting the underlying index should be governed by an independent process in order to avoid conflicts of interest and limit its susceptibility to data or model manipulation, that would affect the payout of the transaction. For example, an independent firm specialized in AI can be used as a ”calculator agent” to assess the value of the index post-disaster.
3. Supervision: The confidence in a disaster index can be improved through active cooperation of regulators or oversight authorities during the design of the index, and when the payments are triggered
4. Transparency: A disaster index should be transparent with an open access to it. It allows to create confidence in its capacity to describe real losses. Wherever possible, the full methodology should be disclosed, and the associated code made publicly available, with clear reference to the data used as input for the calculation.
5. Continuity: The contingency provisions should be provided and documented, in order to ensure the liquidity of the financial products written on the index, especially in the exceptional circumstance of non-availability of satellite data used for the computation of the index.

## 3 IMPACT

Disaster risk insurance increases the long-term resilience of individuals, companies and public entities to external shocks and reduce their short-term future expenditures and failure risks in case of a disaster. It is a social protection at both country and community levels. It helps to mitigate the risk of destitution of people falling into extreme poverty, especially in the most fragile and vulnerable countries. This solution can be implemented in a relatively standardized format ("off-the-shelf" product), thus reducing the cost and efficiency of the structure and consequently granting access to small or poor sponsors.

## 4 EVALUATION

The success can be measured at two levels: the quality of the backtesting and the number and size of financial transactions that are using this new parametric approach based on a Disaster Level Index. First, we have in mind 3-5 specific disasters for which the behavior of the ConvNets based indexes can be tested. The reliability, stability and robustness of the outputs for these 3-5 examples will quantify the first step for success. Second, as the objective is to bring liquidity and standardization (methodology, governance structure, supervision, transparency, and continuity), the large-scale success will be measured by (i) the level of transactions based on this methodology that depends on the buy-in of the main insurance actors (cedents, insurers, and third-party investors), (ii) the ex-post payouts that will be made following disaster events, that will provide resilience and social protection to the affected people.

## 5 RISKS

An unintended risk of the approach is the same as standard parametric insurance: basis risk. It will occurr if the ConvNets based index calculated post-disaster is too disconnected from the actual damages. This risk may be mitigated by introducing the legal option for the insurance buyer to request for an independent assessment based on real losses, in certain circumstances. In this case, the risk for populations is the delayed payout. To avoid any abuse of the system, transparency will be ensured by the publication of the model: algorithm, including the set of hyperparameters (e.g. network structure, number of layers, dimension of each layer, penalty functions, regularization parameters).
The final price would still need to be based on an assessment by the risk taker of the probability of the event to occur by the risk taker, thus not suppressing the need for an actual modelling of the disaster risk (as historical dataset cannot provide a representative sample). Meanwhile, this reduces basis risk.
This type of product would be efficient for certain risks that can be measured by satellite images. Earthquakes or fires are of particular interest. It should be less efficient for others risks (e.g. flood, mudslides).
The index is measuring the occurence of damages but not the actual value of damages. The parametric instrument payout needs to have an assessment of the exposure (location and value) as an input. ConvNet algorithm could be used to qualify the nature and destination of infrastructures, but this is a separate exercise. Satellite images might not be sufficient for a final product as it has limitation (e.g. frequency of high resolution satellite images in certain areas, cloud cover, forest cover). Satellite images might thus be supplemented by additional inputs in the future (e.g. drone images).

## 6 DATA AND LABELS

The dataset for the project can be obtained from public or private satellite image providers, with a focus on developing countries and areas more vulnerable to disasters. Typical data could be 50cm imagery with RGB or 8-Band Multi-Spectral Data, including building footprints (if possible roads and infrastructures). The size of data for backtesting is not expected to be more than approx. 200GB per country or area. The data should be available at two dates: pre- and post-disaster dates. In a second step, more dates could be required to test the stability of disaster indexes based on average observations (e.g. over 10 days). The acquisition of data is under progress through a submission to a collaborative data platform dedicated to development projects. Alternative channels for data acquisition are under study.
If the data include building footprints (if possible roads and infrastructures) for pre- and post-disaster dates, no additional annotation will be required. If they are not directly available, the idea is to discuss their obtention with satellite providers, and funding options may have to be explored.

## 7 SOCIAL AND TECHNICAL SYSTEMS

The core team for this project: (i) Researcher with 20 years experience with Mathematical Economics background (PhD in Finance / Econometrics). Modelling experience, including Deep Learning models. Advanced Python experience, including Keras. (ii) Financial Engineer with 18 years experience with Mathematical background (MSc Eng Ecole Centrale Paris). Experience in disaster risk management products and modelling. (iii) Financial/Data Science Analyst with 7 years experience with Computer Science background (BSc in Computer Science and Engineering, UCLA, and Ms. in Finance from George Washington University). Advanced Python experience, including Keras, NLTK, ScikitLearn.
The technical solution that has been explored uses Python/Keras on a publicly available dataset SpaceNet. We currently have 3 Lenovo desktops Intel Xeon CPU 3.50Ghz with 32.0 GB, with a NVIDIA 2xQuadro M4000 GPU. We could have access to an internal server (80 cores) and hosted servers (AWS, Google Cloud) with more computing capacity if necessary. A residual neural network (ResNet) model has been implemented using SpaceNet data.

## REFERENCES

[1] http://www.africanriskcapacity.org/2016/11/14/press-release-malawi-to-receive-usd-8m-insurance-payout-to-support-drought-affected-families/

[2] http://www.artemis.bm/news/jamaica-questions-ccrif-model-after-floods-fail-to-trigger-policy/

[3] Doshi J., S. Basu, and G. Pang (2018). From Satellite Imagery to Disaster Insights. NeurIPS 2018.

[4] European Securities and Markets Authority (2013), Principles for Benchmarks: Setting Processes in the EU, Consultation Paper, January.

[5] Hillier J., K. Mitchell-Wallace, M. Foote and M. Jones (2017), Natural Catastrophe Risk Management and Modelling: A Practitioner's Guide.

[6] He, Zhang, Ren and Sun (2016). Deep Residual Learning for Image Recognition. IEEE Conference on Computer Vision and Pattern Recognition.

[7] Krizhevsky A., I. Sutskever, and G. Hinton (2012). ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information Processing Systems, (25), pp. 1097-1105.

[8] LeCun, Y., L. Bottou, and P. Haffner (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86 (11), 2278-2324.

[9] Simonyan K. and A. Zisserman (2014). Very deep convolutional networks for large-scale image recognition.

[10] Szegedy C., S. Ioffe, V. Vanhoucke and A. Alemi (2016). Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning, ICLR 2016 Workshop.

[11] Szegedy C., W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich (2014). Going deeper with convolutions.