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Nikolopoulos, Kostas; Petropoulos, Fotios; Sanchez Rodrigues, Vasco; Pettit, Stephen; Beresford, Anthony

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Konstantinos Nikolopoulos * Corresponding Author
forLAB, Bangor Business School

Bangor University

(+44)1248-383-796, Email: kostas@bangor.ac.uk

Fotios Petropoulos

Information, Decision and Operations Division

School of Management

University of Bath

(+44)1225-386-742, Email: f.petropoulos@bath.ac.uk

Vasco Sanchez Rodrigues, Stephen Pettit, Anthony Beresford

Logistics and Operations Management Section

Cardiff Business School

Cardiff University

(+44)2920-874-000, Emails: sanchezrodrigues@cardiff.ac.uk; pettit@cardiff.ac.uk; beresford@cardiff.ac.uk

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A disaster response model driven by spatial-temporal forecasts

Abstract

In this research, we propose a disaster response model combining preparedness and responsiveness strategies. The selective response depends on the level of accuracy that our forecasting models can achieve. In order to decide the right geographical space and time window of response, forecasts are prepared and assessed through a spatial-temporal aggregation framework, until we find the optimum level of aggregation. The research considers major earthquake data for the period 1985 – 2014. Building on the produced forecasts, we develop accordingly a disaster response model. The model is dynamic in nature, as it is updated every time a new event is added in the database. Any forecasting model can be optimized though the proposed spatial-temporal forecasting framework, and as such our results can be easily generalized. This is true for both other forecasting methods, as well as in other disaster response contexts.

Keywords: Disaster Response; Forecasting; Spatial Aggregation; Temporal Aggregation; Earthquakes;

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1. Introduction

The predictability and prediction of major earthquakes has long been the subject of intensive research. The seminal works of Lane (1966) and Whittow (1980), for example, highlight the semi-predictability of earthquakes, showing that they occur intermittently over long periods of time with a tendency not to cluster into short time periods. However, the intensity and timing of an individual earthquake, is very hard to predict (Taleb, 2007).

Questions such as these go 2,500 years back to Ancient Greece when Archimedes described the intermittent nature of earthquake occurrences. Most probably, the exact timing, location or impact of an earthquake cannot be predicted. Trying to focus to a specific location (city/region) and a narrow time interval (day or even week) is impossible. Of course, there are regions that are considered more seismic active, based on plate tectonic movements. For example, it is much more probable that an earthquake of magnitude 5 or greater will occur in Greece compared to UK.

Even if the areas with high seismic activity are taken as the focus, it is again not possible to accurately predict the exact timing or the impact of an earthquake. If the exact location and timing of an earthquake cannot be predicted, then what action can be taken? In summary, at which scale are earthquakes the least predictable, and conversely, at what scale are they most predictable?

With reference to impact, one approach is to try and improve existing response systems so that communities are better prepared should an earthquake occur. In order to improve such systems it might therefore be possible to use aggregation in terms of both time and geographical regions, in order to establish the optimal levels of positioning and stock volumes, that will be used for strategic planning.

In this research, we propose a disaster response model combining preparedness and responsiveness strategies. The selective response depends on the level of forecasting accuracy that we can achieve. In order to decide the right geographical space and time window of response, forecasts are prepared and assessed through a spatial-temporal aggregation framework, until we find the optimum level of aggregation.

The research considers major earthquake data for the period 1985 – 2014. Building on the produced forecasts, a disaster response model is built; the model is dynamic in nature, as it is updated every time a new event is added in the database. Any forecasting model can be optimized though the proposed spatial-temporal forecasting framework, and as such our results can be easily generalized, for other forecasting methods and in other forecasting (disaster) contexts.

The rest of the paper is structures as follows: section 2 provides a short literature review, while section 3 the empirical results. Section 4 provide the disaster response model and policy implications, while the last section concludes and highlights avenues for future research.

2. Literature Review

Our literature review focuses on disaster response and relief logistics as well as earthquake preparedness. We do not focus on listing all possible earthquake forecasting models, as our proposed methodology can be applied and improve any forecasting model. For a review of the respective latter forecasting literature, the reader can follow a series of available articles (Schäfer 2014; Geller 1997; Vere-Jones 1995). Furthermore, we do acknowledge that there is a relevant body of literature coming from actuarial science, but we do consider this out of the scope of this research and direct the interested reader in a series of volumes on predictive modelling techniques, theory, applications and case studies in actuarial science (Frees, Derrig & Meyers, 2014; 2016).

2.1 Disaster Response

In recent years, academic reviews of humanitarian aid and emergency relief logistics have been elevated from essentially descriptive and observational (Pettit and Beresford, 2009; Kunz and Reiner, 2012; Kovacs and Spens, 2011) to methodological and analytical (Naji-Azimi *et al*, 2012; Paul and MacDonald, 2016; Powell *et al*, 2016). The rapid growth in academic interest in the applied field of humanitarian aid and emergency relief logistics, as well as adding energy to the debate, has increased its scale and scope.

The frequency of occurrence of natural disasters in recent decades has led to a growing awareness of their impact on communities and society in general. This, in turn, has triggered increased interest in modelling the predictability of the events themselves, and assessing the degree to which impact can be mitigated by improved levels of preparedness or better responsiveness. Galindo and Batta (2013) and Gutjahr *et al* (2016), for example, have reviewed the growing body of literature in the operational research field which has focused on humanitarian aid distribution or emergency relief provision.

It is suggested that, although modelling has become more sophisticated and increasingly granular, the underlying pattern of research has not significantly changed. Management of disasters in general terms has persisted as one of the main research threads (see, for instance Edrissi *et al*, 2013) and a second thread has followed a case approach looking at, for example, Brazil (Alem *et al*, 2016), Iran (Tofighi *et al*, 2016) or Turkey (Kilci *et al*, 2015).

A third branch of research embraces cross-cutting studies such as that by Ozdamar and Ertem (2015). These embrace several dimensions which include organizational as well as operational parameters. They typically focus on the importance of taking an integrated approach in order to fully understand uncertainty. The papers referred to above, endeavour to make sense of, and parameterize, a range of challenges which are either implicitly, or explicitly, an integral part of the humanitarian logistics problem in different circumstances.

2.2 Earthquake preparedness

The goal of emergency response is to provide shelter and assistance to the victims of disasters as soon as possible after an emergency occurs. Pre-positioning of supplies at strategic locations is essential in ensuring their availability both when required and for faster response (e.g. Rawls and Turnquist 2010; Balcik *et al*. 2010). It has been suggested that in the long run such an approach aids in the reduction of the cost of deliveries to those locations due to regular replenishment (Gatignon *et al*. 2010).

Many studies have addressed the importance of the preparedness phase and the need for pre-positioned warehouses in humanitarian relief logistics, whereas only a small number of papers are related to the location decision (e.g. Rawls and Turnquist 2010; Campbell and Jones 2011). Gatignon *et al.* (2010) illustrate the implementation of a decentralised model at the International Federation of the Red Cross using the pre-positioned warehouse concept. Campbell and Jones (2011) use a cost model to examine the preposition of supplies and the volume of goods in preparation for a disaster. Nevertheless, where the above studies discuss the optimal location based on a single criteria (e.g. minimum total costs), the evaluation process for strategic decisions often involves several attributes and it is usually necessary to make compromises among possibly conflicting tangible and intangible factors (Onut and Soner 2007).

The multi-criteria decision-making (MCDM) approach has been widely adopted as a tool for optimising the location of stocking points for emergency relief goods (see for example Roh et al, 2015). However where and when an emergency event might occur has been considered less frequently, yet is a very important part of effective emergency response.

Prediction of major events in terms of their timing, location and intensity form the focus of the research in this paper. In specific terms therefore the research gap is addressed by specifically considering the overall pattern of humanitarian relief organizations' strategic stocking locations in both international (macro level) and local (micro) contexts in relation to the historic pattern of earthquake occurrence at a global scale. One alternative and more recent approach is that major disasters, and most specific major earthquakes, can be seen as 'peaks over threshold' of a time series that is reporting all earthquakes for a period of time (Leadbetter, 1991). To that end, Nikolopoulos (2020) advocated for the use of intermittent demand forecasting techniques for forecasting such data, and reducing uncertainty when dealing with such extreme events.

Distribution/logistics centre attributes have been discussed by, for example, Li *et al*. (2011) who highlighted parameters such as accessibility, security, connectivity, costs, and proximity to customers and suppliers as key to successful logistics. Although this research was in the context of commercial operations, all of these measures are transferrable to the humanitarian sector. If these measures are superimposed on robust event forecasts their value is maximized.

Locating a pre-positioned warehouse near to the beneficiaries and potential disaster location potentially reduces delivery time and cost. However the facility would be unusable if it was destroyed due to a disaster. The geographical location of the warehouse does not have to be near the disaster prone area, but rather could be in the headquarter country or next to a regional office for strategic reasons.

Proximity to beneficiaries for a potential warehouse is thus one of the important considerations and can be viewed in a similar way with proximity to disaster prone areas. Critical to the question of locating emergency response depots, and hence materials, is having the best possible understanding of the probability of earthquake occurrence as measured by its location, timing and intensity. This can be viewed as a three dimensional construct involving X, Y and Z variables which can be assembled into a three dimensional model.

There is substantial literature on probability forecasting which though mostly outside earthquake prediction, is useful for improving understanding of such three-dimensional models. In the context of weather forecasting, for instance, three-dimensional models are common and outcomes are in the form of probability forecasts. (Palmer, 1999) Central to the application of probability is the level of aggregation of data on both temporal and spatial scales. An example of this is the UK Meteorological Office which has developed techniques to understand such uncertainties, called ensemble forecasts. In this forecasting procedure simulations are run many times rather than just once, with very slight differences in the inputs in order to slightly the starting conditions.

The range of outcomes thus generates a measure of confidence or certainty in the overall forecast (Met Office, 2016). While using ensembles gives an indication of certainty / uncertainty it also creates a problem in communicating the results. The main issue being; how high is the confidence about certain (likely) outcomes in relation to the low confidence in (unlikely) outcomes of low probability?

The key measures in the case of earthquakes, and therefore the parameters of concern for forecasting are: location of occurrence (epicentre), intensity (or power), duration, depth of the disturbance and proximity to areas of population; this last parameter largely determines the impact of the event expressed in terms of material damage or loss of life. The United States Geological Survey National Earthquake Information Center estimates that over a million earthquakes occur in the world each year (NEIC, 2016). Many have no impact because they occur in remote areas which are virtually uninhabited and beyond the reach of detecting mechanisms. Table 1 details the estimated frequency of earthquakes worldwide, according to magnitude and annual average and actual recorded earthquakes.

Clearly, as the scale of earthquake analysis reduces, the more challenging the forecast of 'when, where and how strong' becomes. At a global scale, the total number of earthquakes is reasonably constant, but the predictability of the major earthquakes, especially at a granular level where locations are specified is low. Although earthquakes of magnitude and 6 and above are relatively predictable, earthquakes of magnitudes from 2 to 5.9 are much more variable in terms of frequency per annum. Earthquakes of below 2 magnitude are so small that they are often not detected; these can be neglected and omitted from any analysis as their impact is negligible.

In order for aid agencies to be prepared for relief operations it is clear therefore that any improvement in the understanding of where and when events are likely to occur would improve both locations of pre-positioned warehouse, and from that the speed of response.

Agencies such as the United Nations High Commission for Refugees (UNHCR) already have pre-positioned warehouses which respond to all forms of crisis. (UN, 2015). While this paper only considers the most important locations relative to earthquakes it is recognised that further development of the research to include other disaster types will improve the locational precision of the work.

3. Empirical evaluation

In order to identify the optimal aggregation levels for predicting earthquakes the Significant Earthquake Database is used. This database contains information on destructive earthquakes which meet at least one of the following criteria:

- Moderate damage (approximately $1 million or more)
- 10 or more deaths
- Magnitude 7.5 or greater
- Modified Mercalli Intensity X or greater
- The earthquake generated a tsunami

This research focuses on earthquake events of the last 30 years, 1985-2014. For each earthquake date and country information are available among others. Three temporal and three geographical levels of aggregation are considered. These are depicted in Table 2. "Region" geographical aggregation level refers to the manual categorisation of countries with regard to their relative proximity to tectonic plates' intersections.

For example, Spain, Greece, Turkey, and Algeria belong (among others) in the same region which is specified from the junction of the Eurasian and the African plates. In total, 16 regions are considered.

Table 1. Annual estimate and actual earthquake occurrences by magnitude

		Annual estimate of	**Number of Earthquakes Worldwide**	
Descriptor	**Magnitude**	**Annual**	Average	standar
Great	8 or higher	1	1.31	1.03
Major	7–7.9	17	14.15	3.72
Strong	6–6.9	134	144.46	23.48
Moderate	5–5.9	1,319	1646.92	385.67
Light	4–4.9	c. 13,000	10308.31	2378.78
Minor	3–3.9	c. 130,000	6671.77	3088.62
Very minor	2–2.9	c. 1,300,000	4501.15	1461.67

Source: USGS NEIC (2016)

Table 2. Aggregation levels considered.

Temporal Aggregation	**Geographical Aggregation**
Monthly	Country
Quarterly	Region
Yearly	World

Subsequently, the data are aggregated in order to take into account all possible combinations for temporal and geographical aggregation levels. As a result, monthly, quarterly and yearly time series for all country, region and world levels are created. In total, nine different aggregation strategies are considered. To evaluate the suitability of these aggregation strategies, a small scale forecasting exercise is performed. The 25 first years of data (corresponding to 25 up to 300 data points, depending the level of temporal aggregation) are used to produce forecasts for the next 5 years (60 months).

Forecasts are produced using the Simple Exponential Smoothing method where the parameters are optimised[2]. Forecasts are generated at the respective aggregation level; e.g. using the quarterly-world data to produce 20 (5 years × 4 quarters) point forecasts referring to predictions earthquake events on a global scale. All predictions are then disaggregated to a monthly-country level as to evaluate all strategies by equal means.

Temporal disaggregation takes place assuming equal weights. For example, the yearly forecast is equally distributed in 12 monthly forecasts. This assumption makes sense, as one would not expect that earthquakes occurrences have seasonal and/or trend patterns. Geographical disaggregation is employed using the top-down hierarchical strategy (e.g. Gross and Sohl, 1990; Fliedner, 1999). Disaggregation weights that are directly calculated from the historical averages of the bottom-level series are selected.

[2] Standard smoothing parameter optimisation is applied, through in-sample minimisation of the sum of squared one-step-ahead forecasting errors (Makridakis & Hibon, 2000)

The produced forecasts are contrasted with the withheld actuals of the last 5 years of data. The comparison of the different strategies is based on two error metrics, the scaled Mean Error (sME) and the scaled Mean Absolute Error (sMAE)[3]. The former is a good indication of the bias whilst the latter is appropriate for measuring accuracy. Both measures are based on the scaled error, which is the signed error scaled by the arithmetic mean of the in-sample data:

$$scaled\ error = \frac{Y_{t+h} - F_{t+h}}{(\sum_{i=1}^{n} Y_i)/n}$$

where Y_{t+h} is the actual h-steps-ahead from the forecast origin and F_{t+h} is the respective point forecast. The scaled absolute error is simply the absolute (unsigned) value of the scaled error. sME and same are derived as the simple average (arithmetic mean) over horizons (months, 1..60) and series (countries).

3.1 Results

Tables 3 and 4 present the empirical results of the forecasting exercise. Table 3 presents the results of forecast bias, where values closer to zero indicate more unbiased behaviour. A minus sign designates over-forecasting, whilst a positive refers to under-forecasting. Table 4 presents the results based on sMAE, showcasing the forecast accuracy of the different strategies.

[3] Two metrics are considered here, to avoid critisicm if only one was used – one focusing on bias (ME) and one on accuracy (MAE). As per the literature findings, using more metrics could lead to different results **(**Makridakis and Hibon, 2000). We do used scaled errors to avoid scaling issues and to be consistent with the latest finding in the field as reported and advocated strongly in the seminal paper of Hyndman and Koehler (2006).

In order to show the differences between the level of predictability across the nine aggregation categories an overall mean for forecast accuracy was determined and the difference from the mean either positively or negatively determined. The results of this exercise are shown in Table 5.

From the empirical results presented above, the following observations can be made:

- All forecasts lead to over-estimation of earthquake frequency; point predictions are, on average, larger than the actual number of events.
- Quarterly temporal aggregation level usually underperforms compared to aggregation at both monthly and yearly levels. This is true for both forecast bias and forecast accuracy, apart from the bias performance of the quarterly-world strategy.
- Yearly frequency outperforms monthly and quarterly for country and world levels. At a regional level the most accurate forecast is at a monthly frequency.
- Forecasting at a regional level results in superior forecasting performance compared to other geographical levels.
- The best performance, both in terms of bias and accuracy, is achieved by the monthly-regional strategy.

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Table 3. Forecast bias of each aggregation strategy (closer to zero is better).

Level of aggregation		**Geographical Aggregation**		
		Country	Region	World
Temporal Aggregation	Monthly	-0.45	-0.29	-0.66
	Quarterly	-0.49	-0.38	-0.65
	Yearly	-0.32	-0.32	-0.59

Table 4. Forecast accuracy of each aggregation strategy (lower is better).

Level of aggregation		**Geographical Aggregation**		
		Country	Region	World
Temporal Aggregation	Monthly	2.12	1.96	2.32
	Quarterly	2.16	2.05	2.32
	Yearly	2.00	1.99	2.25

Table 5. Deviation from Mean Level of Aggregation

Type of Aggregation		**Index**		**Deviation**
Geographical	**Temporal**		**Mean**	**%**
Country	Monthly	CM	2.12	-0.47
	Quarterly	CQ	2.16	1.41
	Yearly	CY	2.00	-6.10
Region	Monthly	RM	1.96	-7.98
	Quarterly	RQ	2.05	-3.76
	Yearly	RY	1.99	-6.57
World	Monthly	WM	2.32	8.92
	Quarterly	WQ	2.32	8.92
	Yearly	WY	2.25	5.63
Mean			2.13	

4. A disaster response model

With the forecasts over-estimating earthquake frequency, this suggests that the prediction technique used in this research could be refined further to narrow the gap between forecasts and actual. This can be achieved by substituting exponential smoothing with a series of more advanced methods as the one participating and winning forecasting competitions (Makridakis et al., 2020; Makridakis and Hibon, 2000) like for example variants of the Theta method (Nikolopoulos & Thomakos, 2019; Asimakopoulos &Nikolopoulos, 2000), and then passing them through a spatial-temporal aggregation framework (Nikolopoulos, 2020). While the quarterly measure is weaker, the more focused monthly measure is more appropriate for determining the most appropriate location for the prepositioning of aid as an agency would need to preposition aid in areas where the highest accuracy forecast is.

Also, it is appropriate that yearly levels of aggregation outperform more granular levels of aggregation as it is more likely to be the case that one major event will occur in a yearly time period than that one will occur within a specific month. In order to show the practical relevance of the forecasting procedure to the question of aid pre-positioning, a model is devised (Figure 1) combining levels of resilience, degree of stock centralisation, level of stock holding and the deviation of each forecast from the mean. Each forecast is placed within the model to show which levels of aggregation are the most relevant to the prepositioning concept. As was previously discussed the most appropriate geographical scale is regional and the best temporal scale is yearly. Thus, in populating the model it can be seen that the most robust levels of aggregation are regional-monthly (**RM**), regional-yearly (**RY**) and country-yearly (**CY**).

This has implications for disaster relief supply chain strategies adopted by decision makers. As Figure 1 shows, the country-year, country-monthly (**CM**) and country-quarterly (**CQ**) aggregations of the earthquake data used in the paper required more localised strategies; however, if the country-yearly aggregation level is the one that has more accurate forecast of these three levels of aggregation, so it could be argued that a localised preparedness strategy is required at this level of aggregation, whereas the other strategies require a greater degree of stock centralisation.

All the temporal-world aggregation levels, namely world-yearly (**WY**), world-monthly (**WM**) and world-quarterly (**WQ**), have the least accurate forecast, which seems to be an indication of the need of a more responsive but centralised strategy. The other three aggregation levels, country-monthly, country-quarterly (**RQ**) and regional-quarterly, seem to have smaller deviations from the mean of forecast accuracy values of the nine level of temporal-spatial aggregations including in the study. <u>That is a sign that a hybrid preparedness-responsiveness strategy is required.</u>

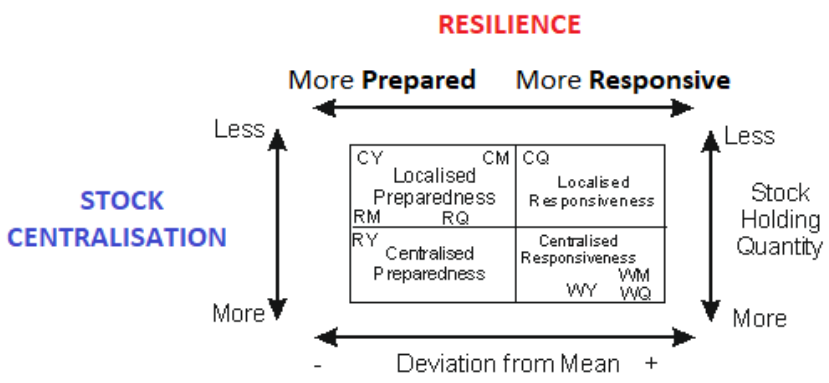

Figure 1. The disaster preparedenes and responsivenees model: Resilience, Stock Centralisation, Stock Holding and Forecast Model

4.1 Implications for practice

There is a clear argument for aid pre-positioning and such strategies are already followed by a range of organisations, for example the UN and the IFRC. There are, however, a number of factors which need to be considered in the overall picture when making decisions on warehouse location, for example facility operations, fixed overheads, staffing and stock levels will all add costs. From a supply chain perspective there is also the need to balance the number of facilities against the increase in inventory holding costs associated with more facilities. The more important discussion therefore relates to how many facilities and which are the most effective locations for them. Earlier modelling based on population suggested that six facilities in Southern Europe, South Central Asia, East Asia, South America, Eastern Africa, and South eastern Asia (Akkihal, 2006).

Western USA, Central America and the southwest Pacific are examples of regions which are conspicuously absent from this list. However, this paper provides new light which could be used for decision making on network redesign of regional disaster relief operations, if other kind of disasters are included in the database and the model is re-run with those disasters

5. Conclusions

The modelling in this paper can guide policymakers and the relief sector in terms of the range of supply chain risk mitigation strategies which can be adopted in the context of disaster relief distribution. The paper argues that an improvement in the prediction[4] of earthquake events through temporal and geographical aggregation could influence the location and size of disaster relief distribution facilities positioned in different world regions, the stock policy adopted to supply areas affected by disasters, and how disaster relief supply chains respond to such special events.

The research can be improved further by adding data for additional natural disaster types such as tsunami, flooding, drought. Aggregating across all disaster types would produce a more robust, although not necessarily, different network configuration. A combination of hazard type, magnitude, and regional characteristics such as population and infrastructure, could improve the disaster "footprint" and assist in predicting inventory locations, ultimately improving the relief system (Akkihal, 2006). This points towards building a composite natural disaster 'heat map' or three-dimensional model as being a natural 'next-step' for this research.

[4] This U-shape in forecasting performance is not surprising from a statistical perspective, where this is commonly known as the bias-variance trade-off. Estimation suffers when not enough data is available (high resolution = high variance). But estimation also suffers from aggregation (low resolution = high bias). The U-shape finding in this research is consistent with this idea.

In these closing statements, we feel compelled to clarify the following: this research is not for the forecasting method to be used per se, when forecasting earthquakes; this can be further improved via switching to other methods. The paper focuses on the strategy that follows once we realize our predictability limits, so it is about risk-mitigation and the disaster relief model that comes after. One could argue that maybe we could forecast better if we use extreme value theory or even maybe other computational intensive methods (Makridakis et al., 2020) – but this is not what we are trying to do here. We have seen evidence in the respective literature that temporal aggregation works well in an intermittent demand context (Nikolopoulos et al. 2011, Nikolopoulos, 2020), and we use it without having an empirical forecasting competition in mind to set – we leave that as future research.

What we strongly argue however, is that temporal and spatial aggregation can give the geographic areas and timeframe within which centralization of resources should take place; and that you cannot achieve through the other alternative forecasting methods that do not consider aggregation. This latter contribution plus the responsiveness/preparedness disaster response model built on that, we consider to be the fundamental contribution of this research. We are adamant it will create the necessary discourse and discussion on the development of similar models, and we do cherish and anticipate such activity.

For the future we also leave the questions arisen when considering the outcomes of this modelling exercise compared to existing strategies. The UN network, for example, is based on all types of disaster not just earthquakes. However, should there be alternative locations for response to different disaster types or does one network covering all disaster types provide a sufficient level of coverage to ensure an effective response at all times? In respect of future research a systematic evaluation of this forecast method against alternative forecasting tools and against current in practice in disaster relief would be fruitful.

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