A Spatio-Temporal Exploration of Significant Earthquakes

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**Abstract**— In this paper, we provide an effective spatio-temporal analysis of significant earthquakes spanning from 1965 to 2016. We highlight how visual displays and human judgement are used heavily in conjunction via a visual analytics approach to aide our analysis helping to result in comprehensive conclusions.

The report utilizes cluster maps and time series to identify temporal patterns, possible seasonality and peculiar time periods. Density-based clustering methods such as DBSCAN and OPTICS are implemented to aide in identifying oceanic hotspots, used in combination with tree maps to identify the most susceptible countries. Time-series analysis is implemented to identify countries expected to receive increased earthquakes in the future through assessment of plate boundaries with risk analysis implemented to locate which countries will become further unsafe. ARIMA models are developed to help predict the total number of earthquakes in following years with close examinations of ACF and PACF plots as well as model diagnostics by consideration of residuals.

We expect the outcomes of this paper to benefit planners in identifying the most at-risk regions whereby construction plans should consider significant earthquake protection. We further hope this aides residents in susceptible regions deciding whether further earthquakes protection measures will be required in the future.

# Problem Statement

Earthquakes are one of the most dangerous phenomena which strike unexpectedly. It is a result of releasing tension at faults where slowly moving tectonic plates get stuck. As Earth’s lithosphere is made up of multiple plates, earthquakes occur frequently worldwide which can cause severe disruptions to services and more destructive impacts such as tsunamis wreaking havoc amongst cities like the Boxing Day Tsunami [1], ultimately leading to loss of life.

Hence, much literature is available focusing on this for example proposals on constructing ‘earthquake-proof’ buildings [2] and developments of deep-learning models for earthquake detection [3]. We aim to answer the following:

1. Is there a detectable seasonality in earthquakes or peculiar years in terms of magnitude?
2. Can we identify the most susceptible countries, and identify countries expected to receive increased impact if earthquakes exhibit a temporal increase?
3. Can we develop a reliable time series model to predict the expected number of earthquakes in following years?

This analysis will prove useful in possibly identifying earthquake patterns and suggesting to planners which countries require more protection to minimize future damages.

The dataset available [4] is suitable as it contains spatio-temporal data on earthquakes spanning from 1965 to 2016 where temporal patterns can be investigated under varying granularities. Multiple datasets will be combined such as plate boundary locations, allowing for spatial assessments of earthquakes along these. Whilst factors such as yearly tectonic plate speed naturally unavailable, our data should nonetheless suffice and combined with over 20,000 observations, provide a detailed analysis.

# State of the Art

Earthquakes have always been a major concern due to its impacts and therefore has various subtopics of interest, for example, developments of earthquake monitoring software [5] and resistant structural engineering [6]. Combined with the rise in visual analytics approaches [7][8], it is now easier to efficiently investigate earthquakes and their consequences.

Azis et al. [9] worked with identical data and used time series plots assessing how numbers of earthquakes varied annually, aggregated by plate boundaries and by time zone. To predict the total number of earthquakes in following years, 152 models were developed; for each of the 24 time zones, there were two time series, a regular time series and its stationary counterpart, similarly for the 52 plate boundaries. A combination of Linear Regression and LSTM Models were deployed, where both models showed varying performance depending on the time zone and plate. Predictive results were primarily considered by assessing R2 values. It was found that stationary models performed better, and hence suggested that further research should look at implementations of stationary time series modelling techniques.

Hence, we plan to implement ARIMA modelling to predict the number of earthquakes in following years and furthermore, use diagnostic visualizations to evaluate model effectiveness which the author did not carry out, and consider time granularity.

Yang et al. [10] explored spatio-temporal properties of earthquakes between 1960 and 2014 using a spatio-temporal scanning technique to identify two kinds of clusters, burst and persistent. This was carried out by modelling the whole space as a spatio-temporal cube, detecting the type of clusters using cylinders, expanding their base and height until a threshold was met. The relative risk of each cluster was calculated. Space-Time Plots were used to visualize clusters as well as two-dimensional spatial plots examining how clusters varied along plate boundaries.

Our spatial methodology will differ here slightly, as we will be using instead OPTICS and DBSCAN Clustering due to their abilities to adapt with geo-spatial data [11][12]. This will be applied on spatial data to eliminate noise and locate clusters of dangerous at-sea earthquake hotspots since most occur off-shore. This report will aid our research as we will similarly be utilizing two-dimensional spatial plots to help visualize clusters.

Graphical user interface, chart, histogram

Description automatically generatedBattul et al. [13] explored spatio-temporal techniques using similar data, for earthquakes between 1912 to 2009 in India. Feature engineering was carried out by binning features such as magnitude, and visualizations such as bar charts and histograms were used to assess distributions of features, as well as spatial visualizations assessing the distribution of earthquakes, colored by binned groups. A linear regression model was fitted examining how numerical features related to earthquake size, visualized by plotting comparisons of true values against predicted.

Whilst some histograms had yielded some conclusions, the author did not consider temporal changes, this would be more meaningful to assess which is what we’ll implement in combination with binning to improve insight. We will also build on this by examining how earthquakes vary given plate boundary locations and examine seasonality via heatmaps.

# Properties of the Data

The dataset was extracted from Kaggle [4] containing 23,230 earthquakes between 1965 and 2016, giving a sufficient timescale to identify patterns, consisting of earthquakes with magnitudes over 5.5 making up 21 features; ‘main’ features included Date, Time, Latitude, Longitude, Depth and Magnitude. Since magnitudes below 5.5 were not included, we implicitly assumed each earthquake was distinct rather than grouped by foreshocks, mainshocks and aftershocks which would be unrepresentative. Spatial features spanned worldwide; in terms of precision, Latitude and Longitude were given to 3 decimal places, sufficient for earthquakes accounting for random error, with Time given down to the second. Remaining features were geology specific for example Earthquake ID and Magnitude Source which were irrelevant, as well as Azimuthal Gap etc. which contained 30% to 99% missing values. Given these proportions and that imputing these would yield unfair analysis, these were dropped. No duplicates appeared.

*Fig. 1 - Histogram of Depth highlighting a small cluster of earthquakes with very deep depths*

Missing value analysis was carried out; only 3 missing values were found for Magnitude Type (the way magnitude was measured), these were imputed using the mode since it made up a miniscule amount. Earthquake magnitudes were measured via different metrics for example Moment Magnitude, Richter Magnitude etc., these measurements are valid for certain frequency and distance ranges; the range of validity for these all lie on the same scale. Where possible, magnitudes were converted to the uniformly applicable Moment Magnitude [14], suitable for large magnitudes. Where conversions were not possible, we implicitly assumed their magnitudes were measured using the Moment Magnitude since previously converted magnitudes did not deviate much from their original values.

Outlier analysis was carried out using histograms and boxplots with the latter acclaimed at its ability to detect outliers [15]. Only Depth exhibited these across the 50 years. Earthquakes with negative depths had their depths set to zero, which were close to 0 anyways. 300 earthquakes were identified with larger than usual depths (Fig. 1) - we decided to not drop these – we interpreted these as rare earthquakes in which we cannot know when or how often they occur, attributed to the Black Swan Principle [16].

Extensive feature engineering was implemented; geocoding was employed to retrieve country names based on latitude and longitude, and subsequently continent names. Around 50% of earthquakes occurred at sea, hence their Country and Continent label was ‘Undefined’. Magnitude and Depth were grouped to create two new features using MTU’s Magnitude Groupings [17] and the USGS Depth Groupings [18] respectively. The Time feature was kept but broken down into Year and Month allowing for analysis over different granularities.

K-Means Clustering was applied using a large number of clusters (40) not for the purpose of clustering, but to create many small groupings of points. By assessing the spatial distributions of each cluster, two new features were created – the Plate Boundary these earthquakes lie on and the Type of Plate Boundary (Convergent, Divergent and Transform). K-Means surprisingly performed well by producing many tight clusters lying precisely on plate boundaries, given that latitude and longitude were used with the algorithm implementing Euclidean distances.

Text

Description automatically generated with low confidence*Table

Description automatically generatedFig. 2 – Description of the final feature set for analysis*

# Analysis

## Approach

We now discuss the analysis approach taken to answer our questions, highlighting how human reasoning with visual displays are repeatedly utilized together to aide our analysis. Fig. 3 summarizes our approach.

Our approach to pre-processing was explained earlier, human reasoning was essential in understanding visualizations like histograms and determining how to analyze outliers in an earthquake context. It was used to engineer a further meaningful dataset through determining suitable numbers of clusters for K-Means and assignment of plate boundaries. It was required to rectify errors during geocoding ensuring correct country assignments, identify suitable magnitude transformations, to make assumptions and ensure a suitable final dataset. We now discuss our analysis in further detail.

To expose possible seasonality and peculiarities, heatmaps will be implemented, human reasoning will be used by examining how magnitudes differ across varying combinations of years and months aiding in seasonality identification. Given the high number of years, time-series plots by both year and month will also be used to help reasoning. Tweaking color schemes of the heatmap also will assist reasoning in identifying peculiar periods by highlighting these in dark colors. Where peculiar periods occur, deeper investigation will be performed providing insight on responsible plate boundaries for increased magnitudes via bar charts aggregated by magnitude group. Spatial visualizations will be utilized, examining most hit

*Fig. 3 – Analysis Approach Workflow*

Table, calendar

Description automatically generatedcountries during these periods, attempting to hypothesize the reasoning behind these using domain knowledge.

Tree-maps will be utilized providing brief ideas of most susceptible countries. Human judgement will be used identifying whether fair conclusions from this can be derived. Given over 50% of earthquakes occur offshore, density-based clustering methods will be implemented using default and tuned parameters (more detail later) to identify spatial clusters at sea visualized using a map. Human judgement will be used identifying oceanic hotspots, further considering how depth and magnitude vary in these regions and considering proximity to countries, in combination with the tree-map helping identify overall vulnerable countries.

In examining countries expected to receive increased impact, temporal visualizations will be used assessing whether increasing trends appear, aggregated by continent. Where trends appear, analysis showing changes in earthquakes numbers on surrounding plate boundaries will be explored, including changes in magnitude and depth assessing risk. Spatial visualization of earthquakes surrounding worsening plate boundaries will be examined using judgement to identify at-risk countries in the future.

Map

Description automatically generatedHuman judgement will be used in deciding the time granularity to predict the future number of earthquakes on; an initial time series plot complimented with its ACF and PACF plots will be made where judgement is required identifying whether differencing is needed. Once differenced, if required, human judgement is needed to determine ARIMA model coefficients based on the (new) ACF and PACF visualizations whereby a model is fitted. Assessment of the model coefficients significances, results of the Ljung-Box and Jarque-Bera Test and examination of residual diagnostics will be done via human judgement. Using the final model, predictions will be done, to be compared to true values whereby conclusions will be made on quality and predictive power.

*Fig. 4 – Heatmap of average magnitudes by Month and Year*

## Process

### Question 1

Heatmap analysis in figure (INSERT) showed average magnitude did not yield trends by month, year or a combination, supported also by time series examinations by year and month even when accounting for magnitude and depth, suggesting absent seasonality supporting expectations that earthquakes unexpectedly strike.

However, the heatmap suggested peculiarities during August 1965, December 1966 and February 1969 exhibiting unusually high average magnitudes.

*Fig. 5 – Barrage of earthquakes hitting Vanuatu with varying magnitudes in August 1965*

August 1965 found the Australian-Pacific boundary primarily responsible here. Analysis showed annually, roughly 65-70% of earthquakes magnitudes are Band 0. With 53% of earthquakes in Bands 1 and 2 with remaining in Band 0 during this period, this explained increases in average magnitude. Highest magnitude earthquakes were concentrated on the Australian-Pacific boundary, with depth mostly shallow. Combinations of high magnitude and shallow earthquakes imply high chances of land damages in close proximity. Spatial analysis showed much of these earthquakes were surrounding Vanuatu which borders the boundary – correlating with literature mentioning Vanuatu being hit with a series of destructive earthquakes then [19].

Similar conclusions yielded compared to August 1965 with most earthquakes focused on the Australian-Pacific plate, including the highest magnitude ones, although a shallow Band 2 earthquake occurred on the South American – Nazca boundary. Most earthquakes were shallow and spatial analysis showed these surrounded Papua New Guinea and Chart, treemap chart

Description automatically generatedVanuatu, as well as a destructive earthquake on the Chilean coast causing $400,000 dollars’ worth of damages (1966 rate) [20].

February 1969 was interesting because whilst there was dominance of higher band magnitude earthquakes like before, with much of the earthquakes focused on the Philippine-Eurasian plate boundary, what was interesting was that strongest earthquakes still occurred on Australian plate boundaries, e.g., Australian-Pacific, with Band 0 earthquakes occurring along Philippine-Eurasian plate and elsewhere. In contrast, earthquakes that occurred along Australian plates were deep depth-wise hence not deemed as destructive due to seismic waves losing energy travelling far to the surface [21]. Spatial visualization showed the Philippines and parts of Indonesia primarily affected here.

*Fig. 6 – An initial tree-map highlighting the most susceptible countries*

In conclusion we observe the source of peculiarity narrowed down to high magnitude earthquakes surrounding the Australian plate in the 60s, where boundaries are convergent, primarily affecting Vanuatu and Papua New Guinea. Since the 60s, earthquake magnitudes surrounding Australian plates have dropped and stabilized to reasonable levels via time series visualizations explaining peculiarities in this period, although no domain literature found explaining why. With insufficient data, we cannot conclude why these boundaries had such high numbers however literature suggested the Australian and Pacific plates are the fastest moving [22], hence we could hypothesize that the plate was moving at its fastest in the 60s and due its speed, huge build-ups of stress were created where the plate got stuck. Once weaker areas of crust slipped, releases of tension created a series of dangerous earthquakes affecting surrounding countries compared to slower moving plates where stress build-up is naturally weaker. We may further hypothesize that since the 60s, this plate speed has slowed down.

### Question 2

Map

Description automatically generatedFig. 6 shows a tree-map showing the most susceptible countries; however, this is unrepresentative. Over 50% of earthquakes occurred offshore, with spatial visualizations showing many earthquakes occurring close to countries where geocoding failed at assigning countries. Spatial visualizations were highly congested, so DBSCAN and OPTICS clustering were employed to identify oceanic hotspots due to flexibilities working with varying distance metrics [11][12]. We will be working with offshore earthquakes here.

Spatial coordinates were given via latitude and longitude, hence the Haversine metric was used in calculating great-circle distances between earthquakes assuming Earth was spherical to develop a distance matrix, first converting spatial data into radians.

A default DBSCAN algorithm was initially implemented – yielding poor results, essentially all points allocated to a single cluster, likely attributed to the epsilon parameter in scikit-learn being unsuitable; DBSCAN results are highly sensitive to epsilon [11] with large values yielding large clusters with less noise and vice versa. Attempts at tuning both the epsilon and minimum number of samples parameters were implemented using heuristic approaches [23][24]. This was our best DBSCAN outcome - clusters resembled plate boundaries, shown in Fig X. Whilst helpful in showing most earthquakes occurred on boundaries, this was still too noisy.

We expected OPTICS would improve results given independence of epsilon and consideration of clusters having local densities [12]. Using the same minimum number of samples as the ‘tuned’ DBSCAN model, results are shown in Fig X, showing improved results with noisier observations such as those far from countries removed, hence easier to identify susceptible countries. Many countries in (south) eastern Asia such as Japan, Indonesia, Papua New Guinea and Vanuatu, and most lying on the west of South America such as Chile and Mexico were found to be highly susceptible alongside New Zealand. Most countries within the Greater Antilles are susceptible and also those around the Mediterranean and Arabian Sea, all of which noticeably lie close to plate boundaries; highlighting why utilizing tree-maps alone were unrepresentative; for example, Japan, known as one of the most susceptible countries, was not reflected in Fig X as nearly all earthquakes happened offshore. By combining the tree-map with above clusters, it was easily identifiable what the most susceptible countries are, namely Japan, Indonesia, Papua New Guinea, Chile, Vanuatu and Philippines in which the latter 5 dominated the tree-map, also exhibiting oceanic hotspots.

Map

Description automatically generatedTime series plots were used assessing changes in numbers of earthquakes annually by continent. All continents showed stability except ‘Undefined’, exhibiting significant increases i.e., rises in offshore earthquakes, prompting temporal examinations of changes in earthquakes aggregated by plate boundary only applied to ‘Undefined’, identifying responsible boundaries. Most boundaries remained stable, except 5 (Australian-Pacific, Caribbean-Cocos, Nazca-Pacific, Antarctic-Pacific and South America-Nazca) exhibiting slow increases which collectively gave significant increases overall. An investigation into risk was done. In all mentioned plates, increases in earthquakes were attributed to rises in Band 0 earthquakes, which were all shallow hence low risk consequences for example light ground shaking. Higher bands of earthquakes remained stable on most plates hence risk levels only marginally increasing for surrounding countries, although the Australian-Pacific and Caribbean-Cocos boundaries are experiencing gradual increases in Band 1 earthquakes alongside, though the depths of these are intermediate so risk levels are also marginal increased.

Whilst risk levels to countries surrounding these boundaries seem unchanged, these countries should expect further earthquakes in the upcoming years primarily the west coast of South America, countries in the Greater Antilles, and those bordering the Australian-Pacific plate such as New Zealand, Vanuatu and Fiji.

### Question 3

The granularity of time was selected to be months, this struck a balance between years and days. Predictions based on year means led to an insufficient 50 data points, with days being too granular leading to a noisy series being too random.

An increasing trend was visible showing the series was not stationary combined with slow decay occurring with points not staying within bounds on the ACF plot at high lags. The trend looked roughly linear or slightly quadratic suggesting testing of first and second differences and comparing results.

Both first and second differenced series looked stationary by visualization of the series albeit some large spikes in the latter likely attributed to introduction of more noise at higher-order differencing, and in ACF plots although this is clearly not perfect with multiple points reaching out of bounds at higher lags, expected with real word data. No pattern was determined with out of bounds spikes, indicating no seasonality.

Considering the first differenced series, one significant spike was shown at lag 1 on the ACF plot, indicating an MA(1) model, supported by exponential decay in the PACF plot shown in Fig X. Fitting this model returned statistically significant coefficients through assessment of p-values. The model passed the Ljung-Box Test [25] for the first 20 lags [26] except the first using 5% significance level, indicating the residual autocorrelations being statistically zero. This is good, we hope model residuals resemble white noise which has this property; however, the model failed the Jarque-Bera Test [27] indicating residuals not following a Gaussian Distribution. Examination of the Kernel Density estimate showed a slight skew and kurtosis supporting this.

*Figs. 7a and 7b – Clustering results obtained from our ‘tuned’ DBSCAN algorithm and OPTICS algorithm respectively*

The second differenced model yielded an MA(2) model through similar examinations, giving similar conclusions in terms of coefficient significance. We observed improved results observed for the Ljung-Box Tests, whilst the Jarque-Bera Test still failed, visualizations of the residual KDE more closely resembled a Gaussian Distribution as well as the raw series visualization albeit some large spikes roughly resembling white noise, with improved skew and kurtosis values, this was our model of choice although not perfect.

Using this model, predictions were made to forecast the number of monthly earthquakes in 2015-2016 as long-term predictions would be unreasonable, fitting a model on 1965-2015 data, shown in Fig X, exhibiting slight increases over the 12 months with predictions, representing roughly the mean of the process. Whilst our predictions were particularly unhelpful, it further supports the randomness of earthquakes highlighting the difficulties in earthquake prediction. In terms of predictive power, empirical evidence shows forecasts via averaging outperforming ARIMA models [28], thus providing a benchmark for earthquakes in following months.

## Results

We concluded that there was no seasonality, both in terms of months and years, successfully supporting expectations that earthquakes strike unexpectedly. Peculiarities during the 60s were identified with increased magnitudes, which narrowed down to high magnitude earthquakes on Australian plate boundaries. Whilst literature on why this occurred during the 60s was unavailable, we developed a suitable hypothesis explaining this phenomenon.

We successfully identified oceanic hotspots particular via OPTICS clustering, which in combination with tree-maps, developed insight into the most susceptible countries, particularly located in East and Southern Asia and South America. Repetitive use of time series visualizations identified countries expecting increased earthquakes, particularly those by the South American-Nazca, Australian-Pacific and Caribbean-Cocos boundaries. A risk analysis via investigation of changes in magnitude band and depth found that these countries should be expecting marginal risk increases than usual, useful for respective residents and planners to prepare suitable earthquake-proofing measures.

Through diagnostics and visualizations, a suitable ARIMA model was developed to predict the number of earthquakes in the short term. We found predictions were not useful with the mean of the process constantly being predicted, although it highlighted the randomness of earthquakes and provided a baseline for future earthquakes useful for earthquake geologists.

# Critical reflection

Heatmap visualizations were a valuable tool allowing magnitude analysis against differing time granularities, aiding reasoning in peculiarity identification and temporal patterns, particularly seasonality. Given high number of years however, the heatmap was crowded, thus alternative visualizations were utilized alongside such as time series visualizations by months and years leading to our conclusion of seasonality. We considered average magnitudes overall, hence disregarded possible temporal trends on a continent or country level or via plate (made possible through feature engineering using K-Means) providing future steps for analysis. For further insight, alongside, changes in magnitude bands could be considered rather than average magnitude, answering our initial research question better, proving further possibly useful to planners for example choosing when to begin construction avoiding major earthquakes.

Feature engineering identifying countries and continents using spatial coordinates proved useful, as geocoding filtered out offshore earthquakes due to inability to assign countries, allowing examinations of earthquake changes at more granular levels such as continent and allowing us to observe that over 50% of earthquakes occurred offshore. Dense spatial visualizations of offshore earthquakes prompted judgement in deducing methods to improve visualizations. DBSCAN and OPTICS were hence implemented to identify oceanic hotspots, eliminating noise. Whilst OPTICS clustering produced impressive results, DBSCAN proved troublesome given high dependencies on epsilon and minimum number of samples. Whilst heuristic approaches improved results, it could not yield expected results, further investigation should be implemented tweaking parameters. Spatial visualizations were useful in deciding meaningfulness of clusters. Other clustering approaches as DENCLUE-IM [29], a DENCLUE variant, could be attempted improving efficiency, since OPTICS took large periods of time, a lesson to remember for future projects. Time series plots proved invaluable in determining risk levels to countries also.

Through repetitive visualizations with judgement via considerations of time series , ACF and PACF plots, we managed to devise a suitable time-series model, deciding how many times to difference and the model type to fit, though residual visualizations and hypothesis test results indicated a slightly imperfect model, expected with real-life data. Whilst predictions were somewhat unhelpful, it provided baselines for future earthquake numbers. Further steps in improving prediction results aside from improving Regression and LSTM approaches [9] include fitting Artificial Neural Networks (ANN) given the non-linear nature of the series; LÖK et al. [30] showed ANN’s performed well predicting smaller earthquakes but struggled on larger magnitude earthquakes attributed to insufficient data. With a dataset three-times larger, applying ANN’s may yield promising results.

Our analysis suffered from limitations however, only containing earthquakes with magnitudes over 5.5, hence unreasonable to group earthquakes by foreshocks, mainshock and aftershocks potentially having allowed examination of how earthquakes spread via foreshocks and aftershocks from the epicenter, interactively via space-time visualizations. Hence, we assumed each earthquake was distinct, not entirely accurate. Geology-specific features were removed given high proportions of missing values; imputation may have benefitted analysis. Missing data on volcanic eruptions meant we could not examine whether an eruption may have caused certain earthquakes or vice versa as these are related, yielding another avenue for analysis.

# Table of word counts

|  |  |
| --- | --- |
| Abstract | 200/200 |
| Problem Statement | 250/250 |
| State of the art | 500/500 |
| Properties of the data | 500/500 |
| Analysis: Approach | 500/500 |
| Analysis: Process | 1500/1500 |
| Analysis: Results | 200/200 |
| Critical reflection | 500/500 |
| **Total Word Count** | **4150/4150** |

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