

Analysis of Geomagnetic A_p Index on Worldwide Earthquake Occurrence using the Principal Component Analysis and Hierarchical Cluster Analysis

(Analisis Geomagnetik Indeks A_p pada Kejadian Gempa Bumi Serata Dunia menggunakan Analisis Prinsip Komponen dan Analisis Kelompok Hierarki)

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ABSTRACT

Geoeffective solar events, especially the coronal mass ejection (CME) and the high-speed solar wind (HSSW) will induce geomagnetic storm upon its arrival to Earth. The solar events could trigger an earthquake occurred during the arrival. In this study, the focus is on the proxy of the geoeffective solar events, which is the geomagnetic A_p index and the data of shallow worldwide earthquakes. The main objective was to investigate the impact of geomagnetic storms on the occurrences of earthquakes from 1994 to 2017 from a statistical perspective. The geomagnetic A_p index data was obtained from the Helmholtz-Centre Postdam - GFZ German Research Centre for Geosciences and the shallow worldwide earthquake data were from the United States Geological Survey (USGS) earthquake catalogue. The Principal Component Analysis (PCA) and Hierarchical Cluster Analysis (HCA) were used to analyse the data. Two groups were obtained from the PCA biplot: Group 1 - before the event (Day-4 to Day-1) and Group 2 - after the event group (Day 0 to Day+4). A two-cluster solution was obtained from the HCA, which shows that days before and after geostorm are divided into two main clusters. The statistical results show that earthquakes activity might have different behaviour before and after the geostorm occurred. In conclusion, the results emphasize that there are differences between days before and after the geostorm occurrence, hence, the solar influence upon earthquake occurrences cannot be neglected entirely.

Keywords: A_p index; earthquake; geomagnetic storm; solar activity

ABSTRAK

Aktiviti geokesan suria yang memberi kesan kepada bumi seperti letusan jirim korona dan angin suria berkelajuan tinggi akan menyebabkan ribut geomagnetik berlaku di Bumi. Aktiviti yang kuat dan geokesan mungkin boleh mencetuskan gempa bumi semasa ketibaannya. Fokus kajian ini adalah pada proksi aktiviti suria yang sampai ke bumi iaitu indeks geomagnetik A_p dan data gempa bumi cetek dari seluruh dunia. Objektif utama kajian ini adalah untuk mengkaji dari perspektif statistik kesan ribut geomagnetik terhadap kejadian gempa bumi tahun 1994 sehingga 2017. Data indeks geomagnetik A_p dimuat turun dari Helmholtz-Centre Postdam - GFZ German Research Centre for Geosciences dan data bagi gempa bumi pula diperoleh daripada katalog gempa bumi United States Geological Survey (USGS). Analisis komponen utama (PCA) dan analisis kelompok hierarki (HCA) telah digunakan untuk menganalisis data. Dua kumpulan diperoleh daripada dwiplot PCA: Kumpulan 1 - sebelum kejadian ribut geomagnetik (Hari-4 hingga Hari-1) dan Kumpulan 2 - selepas kejadian (Hari 0 hingga Hari+4). Melalui HCA, kelompok yang telah diperoleh menunjukkan bahawa hari sebelum dan selepas ribut geomagnetik terbahagi kepada dua kelompok utama. Hasil statistik menunjukkan bahawa aktiviti gempa bumi mungkin dipengaruhi oleh ribut geomagnetik. Kesimpulannya, kertas kajian ini menegaskan bahawa terdapat perbezaan dalam bilangan gempa bumi, sebelum dan selepas kejadian ribut geomagnetik. Oleh itu, pengaruh Matahari terhadap kejadian gempa bumi tidak boleh diabaikan.

Kata kunci: Aktiviti suria; gempa bumi; indeks A_p ; ribut geomagnetik

INTRODUCTION

In recent years, many types of research have been done on the variation of earthquake activities related to solar events and geomagnetic interactions. The advanced

research in the interaction of Sun and Earth encouraged the researchers to investigate this relationship further (Anagnostopoulos & Papandreou 2012; Herdiwijaya et al. 2015; Jusoh 2013; Jusoh et al. 2015; Love & Thomas

2013; Midya & Gole 2014; Nikouravan 2012; Nikouravan et al. 2012; Shestopalov & Kharin 2014; Sukma & Abidin 2016; Urata et al. 2018; Vargas & Kastle 2012). Some researchers have found a correlation between solar events and earthquakes, while others claimed that the earthquake triggered by solar events is irrelevant. Even though extra-terrestrial force may not be as significant as the internal effects such as the movement of tectonic plates or faulting system, it should not be neglectable.

The correlation between solar activity and earthquake events remained unclear, to predict future earthquakes (Love & Thomas 2013). The solar cycle only indicates the sunspots number but not necessarily a geo-effective solar event; hence, to study the solar-terrestrial relation, the solar cycle alone is not enough and must include other variables. Therefore, the relationship between solar activity and earthquake occurrences should be investigated in a more specific manner to understand the phenomenon.

The natural geomagnetic field of Earth may temporarily be disturbed by solar events, which caused a geomagnetic storm. These disturbances were triggered by the high-speed solar wind (HSSW) and the coronal mass ejections (CMEs). The weak-to-moderate geomagnetic disturbances were caused by the HSSW, while the CME increased the disturbance intensities (Chen et al. 2014; Verbanac et al. 2011). In this study, we focused on the A_p index, which is used as an indicator of geoeffective solar events. The primary purpose of this research was to build an understanding of the impact of geoeffective solar events on the occurrences of earthquakes from a statistical point of view.

DATA SELECTION AND METHODS

DATA

The geomagnetic index data and the frequencies of the

earthquakes from 1994 to 2017 were used. The planetary A_p index (in nano Tesla, nT unit) is the most crucial index for forecasting geomagnetic conditions and is the only global magnetic index predicted by the space weather forecasting centres (Paouris & Mavromichalaki 2017). This geomagnetic A_p index is provided by Helmholtz-Centre Postdam - GFZ German Research Centre for Geosciences provides a good indicator for the geoeffective solar activity. A total of 101 storms were obtained where the observation corresponds to the value of the A_p index from moderate to an extreme geomagnetic disturbance (Bartels 1957) with A_p higher than or equal to 57 nT ($A_p \geq 57$ nT). In this paper, we define these as *geostorms*, and the geomagnetic data is obtained from <ftp://ftp.gfz-potsdam.de/pub/home/obs/kp-ap/tab/>. There is a huge gap between 2007 until 2011 due to below the threshold value, which indicates minimum solar activity.

The worldwide earthquakes data were selected with magnitude, $M \geq 4.5$, and depth of foci, $d \leq 70$ km from the United States Geological Survey (USGS) earthquake catalogue. The specific focus here is on shallow crustal earthquakes that are closer to the atmosphere, which responsible for the vast bulk of earthquake damage; subduction-related events will not be discussed in this paper. The outermost layer of the Earth, has a maximum depth of approximately 70 km, with an assumption that the effects of the electromagnetic interaction between the Sun and Earth only affect the crust while the deeper earthquakes are more reliant on the internal geophysical influences (Jusoh et al. 2015).

The number of earthquakes was counted on the day the geostorm happened. In this study, we focused on four days before and four days after the event (Figure 1). Day-0 is defined as the day of the geostorm with $A_p \geq 57$ nT. Hence, the frequency of nine consecutive days with $A_p \geq 57$ which recorded as Day-4, Day-3, Day-2, Day-1, Day-0, Day+1, Day+2, Day+3, Day+4. and a total of 10743 earthquakes occurrences with 101 geostorm observations.

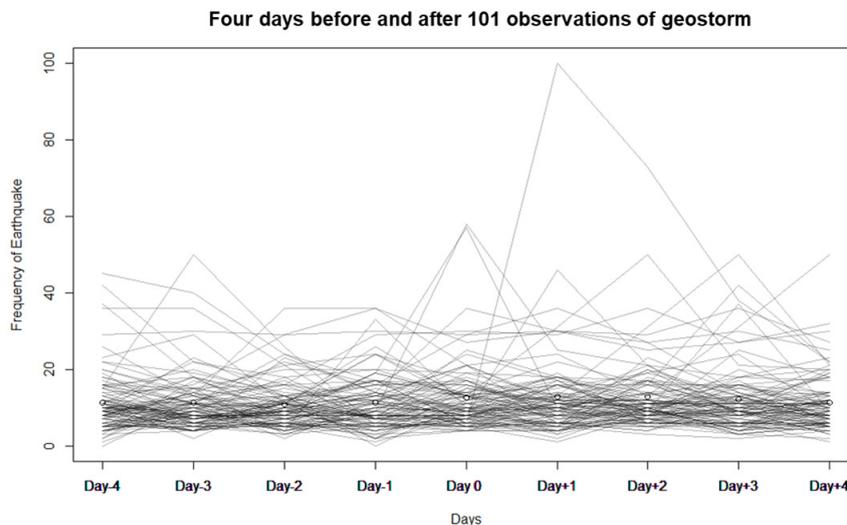


FIGURE 1. The frequency of earthquake on days with geostorm (Day 0), four days before and after the storm (± 4 days). Each line represents one geostorm observation

STATISTICAL METHODS

PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA helps to reduce the dimension, which consists of correlated variables, and it creates an uncorrelated variable and explains much of the variation (trends and patterns) in the original dataset (Lever et al. 2017). It has been applied commonly and widely in many fields such as atmospheric physics, biology, and geology (Jolliffe & Cadima 2016; Mostapha et al. 2018). This method summarizes the features into descriptive rather than inferential. There are no distributional assumptions needed and can be applied to various types of numerical data (Jolliffe 2013). It is a projection method, which finds projections of maximal variability. It seeks linear combinations of the columns of data \mathbf{X} , where \mathbf{X} is 101×9 matrix. Suppose \mathbf{S} denotes the covariance matrix of \mathbf{X} and

$$n\mathbf{S} = (\mathbf{X} - n\mathbf{1}\mathbf{1}^T\mathbf{X})^T (\mathbf{X} - n\mathbf{1}\mathbf{1}^T\mathbf{X}) = (\mathbf{X}^T\mathbf{X} - n\bar{\mathbf{x}}\bar{\mathbf{x}}^T),$$

where

$$\bar{\mathbf{x}} = \frac{\mathbf{1}^T\mathbf{X}}{n},$$

and $\bar{\mathbf{x}}$ is the row vector of means of the variables. Then, the sample variance of a linear combination $\mathbf{x}\mathbf{a}$ of a row vector \mathbf{x} is $\mathbf{a}^T\mathbf{\Sigma}\mathbf{a}$.

The sample variance is maximized subject to $\mathbf{a}^T\mathbf{a} = 1$. The non-negative and Eigen decomposition gives

$$\mathbf{\Sigma} = \mathbf{C}^T\mathbf{\Lambda}\mathbf{C}$$

where $\mathbf{\Lambda}$ is a diagonal matrix of (non-negative) eigenvalues in decreasing order. Suppose \mathbf{b} is a vector with the same length as \mathbf{a} since \mathbf{C} is orthogonal. Likewise,

$$\mathbf{b}^T\mathbf{\Lambda}\mathbf{b} = \sum \lambda_i b_i^2$$

is maximized subject to $\sum b_i^2 = 1$. The variance is maximized either by taking \mathbf{b} to be the first unit vector or considering \mathbf{a} to be the column eigenvector corresponding to the largest eigenvalue of $\mathbf{\Sigma}$. By taking the subsequent eigenvectors will give combinations with as large as possible variances that are uncorrelated with the previous principal component.

In summary, it is the eigenvectors and eigenvalues that are most valuable in PCA. The eigenvectors of the covariance matrix are the directions of the axis where there is most variance (information) which can be called as principal components. And coefficients attached to the eigenvectors are the eigenvalues that give the amount of

variance carried in each component. The initial dataset can be reframed in terms of eigenvectors and eigenvalues without altering the underpinning information. Reframing a dataset does not mean modifying the data itself, it just means that it is looked at from a different perspective which will reflect the data better. The resulting PCA plot will easily identify how many main groups are significant and which one the profile will fall into. Moreover, the projected data in such plots often appear less noisy, which enhances pattern recognition and data summary. Such PCA plots are commonly used to find potential clusters (Jolliffe & Cadima 2016).

HIERARCHICAL CLUSTER ANALYSIS (HCA)

The cluster analysis is found useful to deal with the task of finding a group of interest (Adolfsson et al. 2019; Alkarkhi & Alqaraghuli 2019; Kaufman & Rousseeuw 2009; Larose 2005). Generally, the motivation for clustering is the analysis of data and pattern recognition, storage, search, and retrieval. Clusters are required to be well separated, which means that the objects within the same cluster should resemble one another, and separation of the objects in different clusters should differentiate one from the other (Hansen & Jaumard 1997; Wilks 2011). In this study, the aim is to see the clustering of the earthquake frequency in nine consecutive days (Day-0 and Day \pm 4) that would identify which days are affected significantly by the intense geomagnetic disturbance and which days are not affected.

Cluster analysis (CA) is a multivariate tool used to arrange a set of data (observations, objects) into groups called clusters (Alkarkhi & Alqaraghuli 2019). The observations within each group are almost similar to each other, but the clusters themselves are very different. Clustering is one of the vital data mining methods for discovering knowledge in multidimensional data. The goal of clustering is to identify patterns or groups of similar objects within a data set of interest (Kassambara 2017). The number of clusters is unknown before starting the clustering process. CA is valuable for classifying and identifying the true groups. The clustering approach used in this study is the agglomerative hierarchical clustering. In agglomerative clustering, each observation is initially considered as a cluster of its own (leaf). Then, the most similar clusters are successively merged until there is just one single big cluster (root). These methods calculate the distances of an individual to all the other individuals to form a matrix called the distance matrix. The result of hierarchical clustering methods is presented in a diagram called a *dendrogram*.

RESULTS

The summary statistics of earthquake frequency from Day-4 until Day+4 is presented in Table 1. The dispersion of the observation is calculated along the mean line for each of the observations. In Figure 2, the pale grey colour lines represent all 101 observations, while the solid black

line is the mean, and the dashed/dotted black lines are the upper and lower bounds for the 95% confidence interval. The dashed/dotted black lines show the limit of the location that the points of observation should locate around the mean line, and all the observations located outside the limits are considered outliers. From this plot, we found 45 observations were outside the limits.

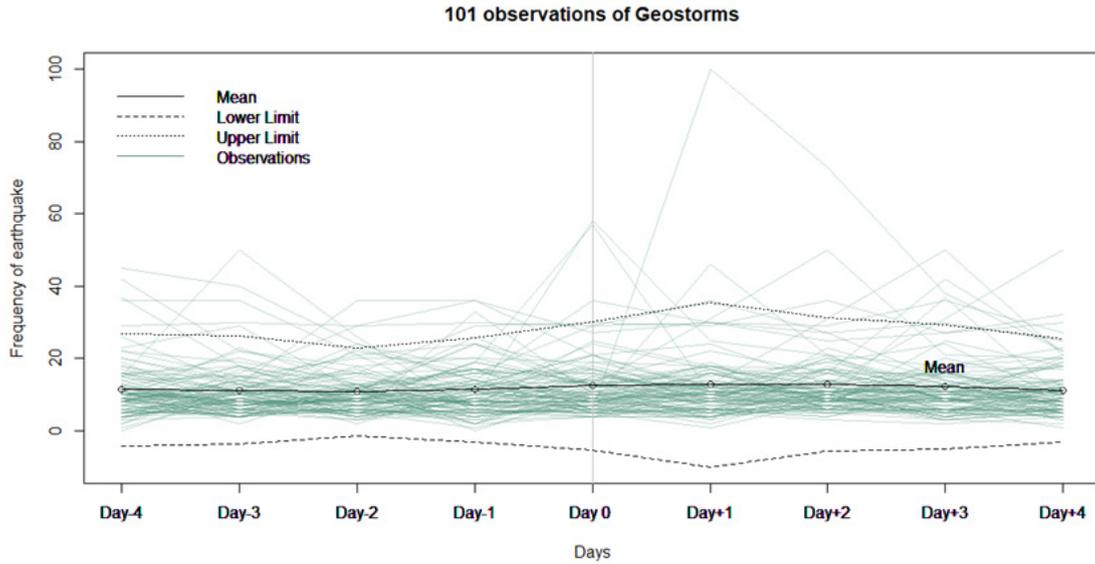


FIGURE 2. Earthquake frequencies for four days before and after the 101 geostorm observations (The grey lines are the 101 observations of geostorm, the solid black line is the mean, the dashed and dotted lines are the lower and upper bounds for the 95% confidence

TABLE 1. The Mean, Standard Deviations (SD) and Standard Errors (SE) for Day±4

	Day-4	Day-3	Day-2	Day-1	Day 0	Day+1	Day+2	Day+3	Day+4
Mean	11.356	11.238	10.832	11.337	12.525	12.752	12.881	12.228	11.218
Standard Deviation	7.939	7.607	6.232	7.361	9.030	11.597	9.423	8.784	7.286
Standard Error	0.790	0.757	0.620	0.732	0.898	1.154	0.938	0.874	0.725

PRINCIPAL COMPONENT ANALYSIS (PCA)

The PCA is to reduce dimension in the data due to correlation in Day variable. Since the data only consists of 9 variables (Day -4 to Day 4), we want to explore the

relationship among observed variables. The number of principal components in the rotation is equal to the number of variables in the dataset. In Table 2, we obtained nine principal components (dimensions), known as PC1-9.

Each of these explains a percentage of the total variation in the dataset. The results show that PC1 has about 55% of the total variation, meaning almost half of the information in the dataset can be explained by just one principal component, while PC2 explains around 14% of the variance. By combining the two principal components, almost 69% of the variation of the data can be explained by these two principal components.

Figure 3 displays the proportion of the total variation explained by each of the components in the principal

component analysis. It also helps to identify how many of the components are needed to summarise the data. From Table 2, we found only PC1 and PC2 with more than one eigenvalue, and from the scree plot, it shows that PC1 and PC2 have a higher percentage of explained variance compared to other components. Hence, PC1 and PC2 are considered enough to explain the data.

Figure 4 shows the variable biplot. Variables with similar characteristics/profiles are grouped together. Two clusters are obtained: Before the event (Day-4 to Day-1) and after the event group (Day 0 to Day+4).

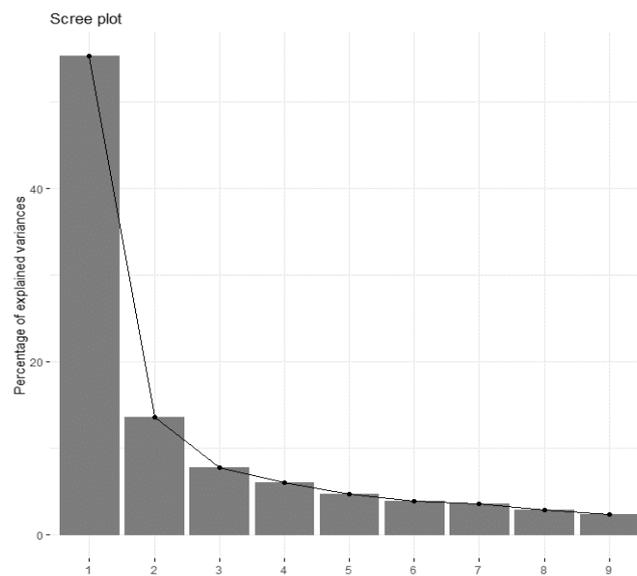


FIGURE 3. Scree plot showing the percentage of explained variances for each principal component (dimensions)

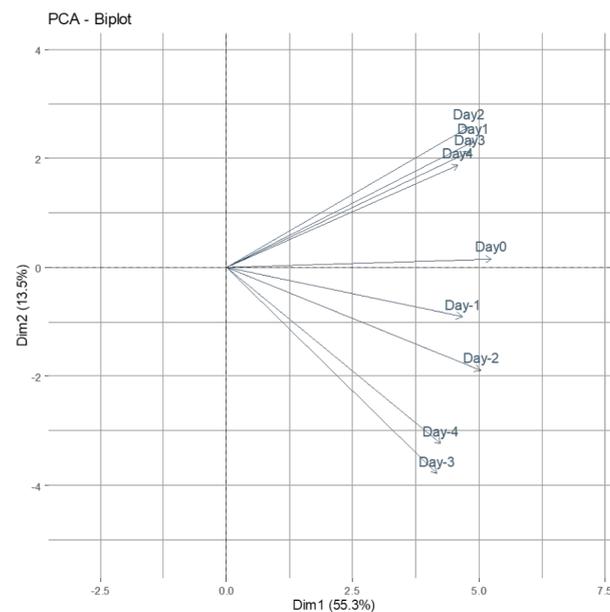


FIGURE 4. PCA biplot for the nine variables (Day-4 until Day+4)

TABLE 2. Dimensions, eigenvalues, percentage of total variation and percentage of cumulative variance

Dimension	Eigenvalue	Total variation (%)	Cumulative variance (%)
Dim.1	4.978	55.309	55.309
Dim.2	1.219	13.545	68.854
Dim.3	0.698	7.760	76.614
Dim.4	0.543	6.037	82.651
Dim.5	0.422	4.693	87.343
Dim.6	0.348	3.872	91.215
Dim.7	0.322	3.583	94.798
Dim.8	0.254	2.823	97.621
Dim.9	0.214	2.379	100.000

HIERARCHICAL CLUSTER ANALYSIS (HCA)

We classify the variables into days around the geomagnetic storm events (before and after the storm). Clustering analysis is a method to identify a set of objects that belong to the same group. The objects in a specific cluster share the same characteristics but different to object that did not belong to the same cluster. Our dataset was divided into nine variables. The first variable is defined as the number of earthquakes with the most intense geostorm denoted as Day-0. The other variables are defined as the frequency of earthquakes on days before and after the event of a geomagnetic storm (“Day-1 and Day+1, respectively).

A dendrogram plot is easier to interpret, where it shows the distance level at which there was a combination of objects and clusters, as shown in Figure 5. The vertical axis is labelled height which refers to the ‘Euclidian distance’ or dissimilarity, d_{ij} between the variables i and

j which we defined as in (1) (Unal et al. 2003) with N is the number of data points in full data period, M is the available data points, and x is the location of each point.

$$d_{ij} = \frac{N}{M} \sum_{k=1}^M (x_{ik} - x_{jk})^2$$

The dendrogram in Figure 5 was obtained by applying the ‘complete’ linkage method, which has the advantage of avoiding the chaining problem. Based on the dendrogram, we can see that four days before the geostorm (Cluster 2) and four days after the geostorm (Cluster 1) are nicely separated into two clusters if we set the distance of 15.9 to cluster the variables that have similar behaviour. The two different clusters mean that the earthquakes activity might have different behaviour before and after the geostorm occurred.

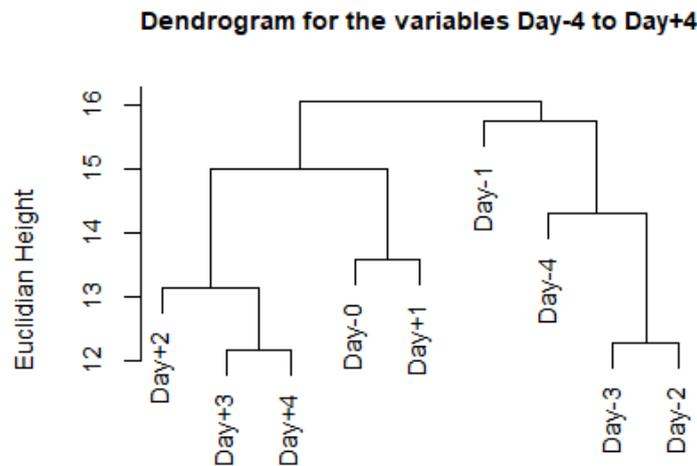


FIGURE 5. The Dendrogram of the earthquake frequency on days before and after the event of geostorm

DISCUSSION

The solar-terrestrial relation involves many complicated processes and systems. Therefore, the results obtained must be interpreted with caution. The results of this study do not explain the behaviour of the earthquake with the occurrence of geostorm. Nevertheless, the present findings are significant in at least a couple of substantial aspects: The pattern of earthquake occurrences is different before and after the geostorm: PCA - two clusters are obtained: before the event (Day-4 to Day-1) and after the event group (Day 0 to Day+4). HCA - clearly shows differences between the days before and after the geostorm (producing two major clusters). Based on Table 3, the number of earthquakes before and after the geostorm differ. The active seismic region (faults and plate boundaries) is not as many as in the lower or mid-latitude, for higher latitude, the occurrences increased after the geostorm compared to the days before. Note that geostorm is not the leading cause

but only one of many possible triggers of an earthquake. For an earthquake to be induced, we need to consider the possible mechanisms, types of rocks of the region, what type of boundaries, and faults. However, it is a fascinating idea to further this study by focusing on the higher latitude region as the effect of geostorm is more prominent at the poles.

The limitation of this study is that it only provides qualitative results (the groups and clusters). Interpretation of such information can be judgemental and biased. Hence it would be difficult to interpret the results for a generalized population of data accurately. Despite the limitations, this study is critical because the findings can provide further evidence that there are differences between days before and after the geostorm occurrence, hence, we cannot neglect the solar-terrestrial influence upon earthquake occurrences.

TABLE 3. Frequency of earthquake with latitudes before and after geostorm

Latitude	Earthquake frequency	
	Day minus (Before)	Day 0 and plus (After)
-90° < Latitude < 90°	4521	6222
High Latitude ≥ 50°	358	376
Low Latitude ≤ -50°	184	193
-50° < Mid Latitude < 50°	3979	5653

CONCLUSION

The 101 geostorm cases and the frequency of earthquakes were taken from 1994-2017 and statistically analysed. The differences in data structure between days before and after the geostorm events are shown in the PCA biplot (Figure 4) and HCA dendrogram (Figure 5). It is demonstrated that the day with the geostorm and the days after the event were grouped into two different clusters. From the findings, we cannot neglect the effects of solar events and geomagnetic storms on the occurrences of earthquakes. This research is still far from using the geomagnetic disturbance as an earthquake prediction mechanism. However, one can expect a variation of seismic activities when the Earth's magnetic field experience major disturbance from the Sun itself.

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REFERENCES

- Adolfsson, A., Ackerman, M. & Brownstein, N.C. 2019. To cluster, or not to cluster: An analysis of clusterability methods. *Pattern Recognition* 88: 13-26.

- Alkarkhi, A.F.M. & Alqaraghuli, W.A.A. 2019. *Easy Statistics for Food Science with R*. Chennai, India: Elsevier, Inc. pp. 177-186.
- Anagnostopoulos, G. & Papandreou, A. 2012. Space conditions during a month of a sequence of six $M > 6.8$ earthquakes ending with the tsunami of 26 December 2004. *Natural Hazards & Earth System Sciences* 12(5): 1551-1559.
- Bartels, J. 1957. The technique of scaling indices K and Q of geomagnetic activity. In *Annals of the International Geophysical Year*. Vol. IV. Fitzroy Square, London: Pergamon Press. pp. 215-226.
- Chen, Y., Liu, L., Le, H. & Wan, W. 2014. Geomagnetic activity effect on the global ionosphere during the 2007-2009 deep solar minimum. *Journal of Geophysical Research: Space Physics* 119(5): 3747-3754.
- Hansen, P. & Jaumard, B. 1997. Cluster analysis and mathematical programming. *Mathematical Programming* 79(1): 191-215.
- Herdwijaya, D., Arif, J., Nurzaman, M.Z. & Astuti, I.K.D. 2015. On the possible relations between solar activities and global seismicity in the solar cycle 20 to 23. In *AIP Conference Proceedings*. AIP Publishing LLC. 1677(1): 050003.
- Jolliffe, I.T. 2013. *Principal Component Analysis*. New York: Springer Science+Business Media, LLC. pp. 199-222.
- Jolliffe, I.T. & Cadima, J. 2016. Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 374(2065): 20150202.
- Jusoh, M.H. 2013. Solar activity and seismicity. Kyushu University. Ph.D. Thesis (Unpublished).
- Jusoh, M.H., Kasran, F.A.M., Liu, H. & Yumoto, K. 2015. Possible correlation between exogenous parameters and seismicity. In *7th International Conference on Recent Advances in Space Technologies (RAST)*. IEEE. pp. 525-529.
- Kassambara, A. 2017. *Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning*. Volume 1 of multivariate analysis. STHDA. pp. 91-126.
- Kaufman, L. & Rousseeuw, P.J. 2009. *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken, New Jersey: John Wiley & Sons, Inc. pp. 126-163.
- Larose, D.T. 2005. *Discovering Knowledge in Data: An Introduction to Data Mining*. Hoboken, New Jersey: John Wiley & Sons, Inc. pp. 27-40.
- Lever, J., Krzywinski, M. & Altman, N. 2017. Points of significance: Principal component analysis. *Nature Methods* 14: 641-642.
- Love, J.J. & Thomas, J.N. 2013. Insignificant solar-terrestrial triggering of earthquakes. *Geophysical Research Letters* 40(6): 1165-1170.
- Midya, S.K. & Gole, P.K. 2014. Trend of major earthquakes during the period 1900-2011 and its association with some solar and geomagnetic parameters. *Indian Journal of Physics* 88(1): 1-4.
- Mostapha, M., Abu Jahar, N., Azizan, K.A., Zakaria, S., Aizat, W.M. & Jaafar, S.N.S. 2018. Proteomic analysis of stored core oil palm trunk (COPT) sap identifying proteins related to stress, disease resistance and differential gene/protein expression. *Sains Malaysiana* 47(6): 1259-1268.
- Nikouravan, B. 2012. Do solar activities cause local earthquakes? *International Journal of Fundamental Physical Sciences* 2(2): 17-20.
- Nikouravan, B., Rawal, J.J., Sharifi, R. & Nikkiah, M. 2012. Probing relation between solar activities and seismicity. *International Journal of the Physical Sciences* 7(24): 3082-3088.
- Paouris, E. & Mavromichalaki, H. 2017. Interplanetary coronal mass ejections resulting from earth-directed CMEs using SOHO and ACE combined data during solar cycle 23. *Solar Physics* 292(2): 30.
- Shestopalov, I.P. & Kharin, E.P. 2014. Relationship between solar activity and global seismicity and neutrons of terrestrial origin. *Russian Journal of Earth Sciences* 14(ES1002): 1-10.
- Sukma, I. & Abidin, Z.Z. 2016. Study of seismic activity during the ascending and descending phases of solar activity. *Indian Journal of Physics* 91(16): 595-606.
- Unal, Y., Kindap, T. & Karaca, M. 2003. Redefining the climate zones of Turkey using cluster analysis. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 23(9): 1045-1055.
- Urata, N., Duma, G. & Freund, F. 2018. Geomagnetic Kp index and earthquakes. *Open Journal of Earthquake Research* 7(1): 39-52.
- Vargas, C.A. & Kastle, E.D. 2012. Does the sun trigger earthquakes? *Natural Science* 4(8): 595-600.
- Verbanac, G., Vršnak, B., Veronig, A. & Temmer, M. 2011. Equatorial coronal holes, solar wind high-speed streams, and their geoeffectiveness. *Astronomy & Astrophysics* 526: A20.
- Wilks, D.S. 2011. *Statistical Methods in the Atmospheric Sciences*. 3rd ed. Oxford: Elsevier, Inc. pp. 603-616.
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