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Winter 2025/2026

Using Meteorological and Geospatial Data to Investigate November 2013 Typhoon Haiyan's Impact in the Philippines

By Charles Wang

AUTHOR BIO

Charles Wang is a high school junior at Hong Kong International School. His passion for science motivates him to lead the school's mathematics and chemistry clubs. He hopes advances in machine learning and data science will accelerate breakthroughs in environmental studies and climate research. His interest in typhoons arises from how often they strike his region. In his free time, he enjoys solving Rubik's cubes and watching STEM videos on YouTube.

ABSTRACT

Typhoons (also known as hurricanes or tropical cyclones) can cause widespread destruction, particularly in vulnerable countries like the Philippines. Historical impact data provide valuable insights into factors influencing typhoon damage and can help improve disaster response by identifying heavily and mildly affected areas. This study utilizes Google Earth Engine to access and analyze meteorological and geospatial data in early November 2013, at the municipal level for Typhoon Haiyan, one of the most destructive typhoons in recent history. Hazard impact data from the National Disaster Risk Reduction and Management Council (NDRRMC) were analyzed using correlation, multiple linear regression, and clustering methods. Results indicate that windspeed and rainfall are dominant factors in determining the percentage of persons affected. Clustering analysis reveals that municipalities experiencing windspeeds exceeding 11.51 m/s suffered the greatest impacts. These findings highlight important factors influencing variability in typhoon impacts. This approach offers a useful framework for rapid impact assessment of future typhoons in the Philippines and elsewhere.

Keywords: *Tropical cyclones; Natural disaster; Typhoon Haiyan; Google Earth Engine; Geospatial data; Hazard Impact; Disaster risk reduction; windspeed; Clustering*

INTRODUCTION

Typhoons, also known as hurricanes or tropical cyclones, rank among the most destructive natural hazards on the planet. Storms are called hurricanes when they form in the Atlantic Ocean or the northeastern Pacific Ocean, typhoons in the northwestern Pacific Ocean, and tropical cyclones in the Indian Ocean and South Pacific. Over the past 50 years, typhoons have caused more than 700,000 deaths and inflicted over one trillion USD in damages. Typhoons are particularly dangerous due to their multiple hazards, such as extreme winds, heavy rainfall, storm surges, flooding, and tornadoes. In addition, climate change has been linked to increased frequency and destructive power of major typhoons (WMO, 2022).

The Philippines is one of the countries that is most vulnerable to typhoons. On average, 20 typhoons enter the Philippine Area of Responsibility (an area where the Philippines' government monitors weather occurrences) each year, with eight or nine making landfall in the Philippines (Santos, 2021). Between 2010 and 2019, typhoons in the Philippines caused 8 billion USD in damages (*Damages due to Natural Extreme Events and Disasters Amounted to PhP 463 Billion*, 2020). From October 24 to November 18, 2024, six typhoons struck the country, affecting over 16 million people, displacing over 11 million people, and causing 274 million USD worth of damage (2024 Typhoon Season WFP Philippines Response Report, 2025). In addition, both the number of extreme typhoons, defined as those with maximum sustained winds above 150km/h, and the associated damage costs have both shown an increasing trend over recent years (Cinco et al., 2016).

Typhoon Haiyan (local name Yolanda), the typhoon studied in this paper, struck the Philippines on November 8, 2013. It was chosen as a case study for this paper because it was the most powerful, destructive, and deadly typhoon that made landfall in the Philippines in recent history (Lagmay et al., 2015). Typhoon Haiyan, along with its powerful storm surges, affected more than 16 million people, displaced around 4 million, injured nearly 28,000, and caused more than 6,300 deaths (Typhoon Haiyan (Yolanda), 2023). In addition, it caused severe damage to buildings and infrastructure, damaging roughly 1.4 million buildings and causing around 770 million USD in damage (Chaivutitorn et al., 2020).

A number of climatic and socio-environmental factors have been recognized as key determinants of typhoon impact, such as elevation, windspeed, rainfall, distance to coast, and social vulnerability index.

Windspeed is a dominant factor in disaster loss for typhoons, and is often used to characterize typhoon intensity. Typhoons with higher windspeeds carry more energy, which leads to greater potential for destruction. Consequently, as maximum windspeed increases, damage and economic loss increase (Kim et al., 2018; Kim et al., 2020; Li et al., 2022; Ye et al., 2020).

Rainfall, a significant characteristic of typhoons, strongly influences the extent of typhoon impact. As rainfall increases, the impact of typhoons also increases. Rainfall can lead to flooding, landslides, and water-related destruction (Kim et al., 2018). One study concluded that differences in accumulated rainfall accounted for most of the vulnerability changes observed between two typhoons, highlighting the critical role that rainfall plays in determining overall typhoon losses (Li et al., 2022).

Distance to the coast is important in determining vulnerability to typhoons, flooding, and storm surges. Coastal areas typically experience stronger winds and more severe storm surges than inland regions. Consequently, the impact and damage caused by typhoons usually decrease as the distance from the coast increases (Kim et al., 2018; Kim et al., 2020).

Elevation is another important factor in determining the severity of typhoon damage. Low-lying coastal areas are highly vulnerable to storm surges, while higher elevations are more exposed to intensified winds and heavy rainfall that can trigger landslides and flooding (Tam, 2017; McCallum et al., 2013; Ransom, 2013), and following Hurricane Sandy, US government took steps to create coastal elevation dataset with enhanced accuracy to improve the ability to forecast flooding (Ransom, 2013).

Many socio-economic factors—such as building quality, population density, and economic status—significantly influence typhoon vulnerability. For example, communities with higher economic status have more access to employee benefits, such as health insurance, which enhance resilience and recovery after a typhoon strikes. This study uses the Social Vulnerability Index (SVI), which is the first national-level measure of social vulnerability at the municipal scale in the Philippines (Lloyd et al., 2022).

This study aimed to conduct an in-depth analysis of the above factors influencing typhoon impacts, focusing on how these factors drive regional differences in impacts from a single typhoon. By concentrating on one typhoon, hazard impact data at the municipal level—the finest granularity available—were obtained along with the relevant factors. Focusing on Haiyan, one of the most destructive typhoons, and a commonly used hazard impact metric, persons affected, provided a substantial amount of valid data points for meaningful analysis. The data analysis first examined whether the municipal-level data of Typhoon Haiyan corroborate prior research on how these factors influence typhoon impacts. Subsequently, the study explored additional analyses that might quantitatively predict the percentage of persons affected.

MATERIALS AND METHODS

Data Acquisition

To analyze typhoon impact and identify potential relationships, this study first collected meteorological data on Typhoon Haiyan and geophysical data for the Philippines through Google Earth Engine's data collections. Hazard impact data for Typhoon Haiyan were then gathered and matched by the municipality. A linear regression analysis was conducted, using the meteorological and geophysical data as independent variables and typhoon impact data as the dependent variable, to determine the most significant factors influencing typhoon impact. Finally, K-means clustering was applied to the two most impactful variables to uncover any natural groupings or patterns within the dataset. K-means clustering was chosen because it effectively identifies inherent groupings in data.

Google Earth Engine

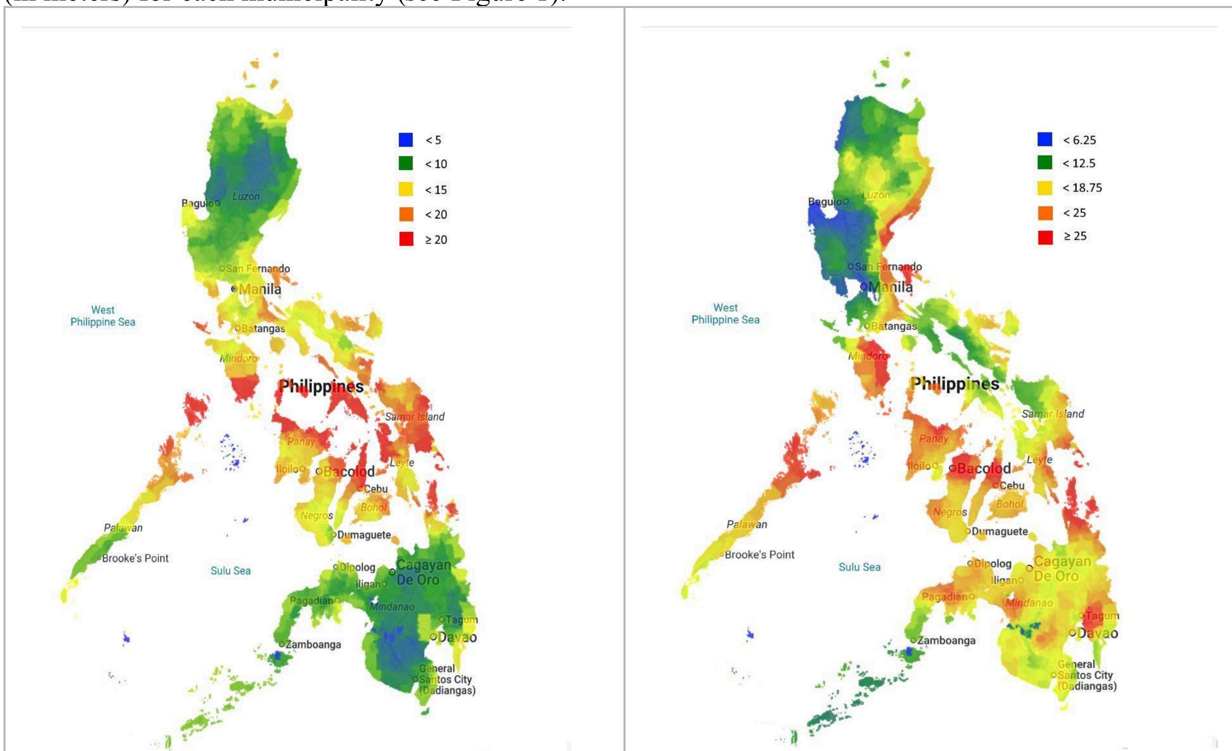
Google Earth Engine (GEE), a platform for scientific analysis and visualization of geospatial datasets, hosts a multi-petabyte catalog of satellite imagery and geospatial datasets with planetary-scale analysis capabilities (Google Earth Engine, 2019). In this study, GEE was used to access and aggregate data on rainfall, windspeed, elevation, and distance to the coast. In addition, it is also used to create

Figures 1, 2, and 4 from the data. Specifically, windspeed and rainfall data were sourced from the ERA5-Land Hourly dataset by ECMWF Climate (Muñoz Sabater, 2019). Elevation data came from the WorldDEM™-30, based on the German TanDEM-X mission data produced by Airbus Defence and Space GmbH (Becek et al., 2016).

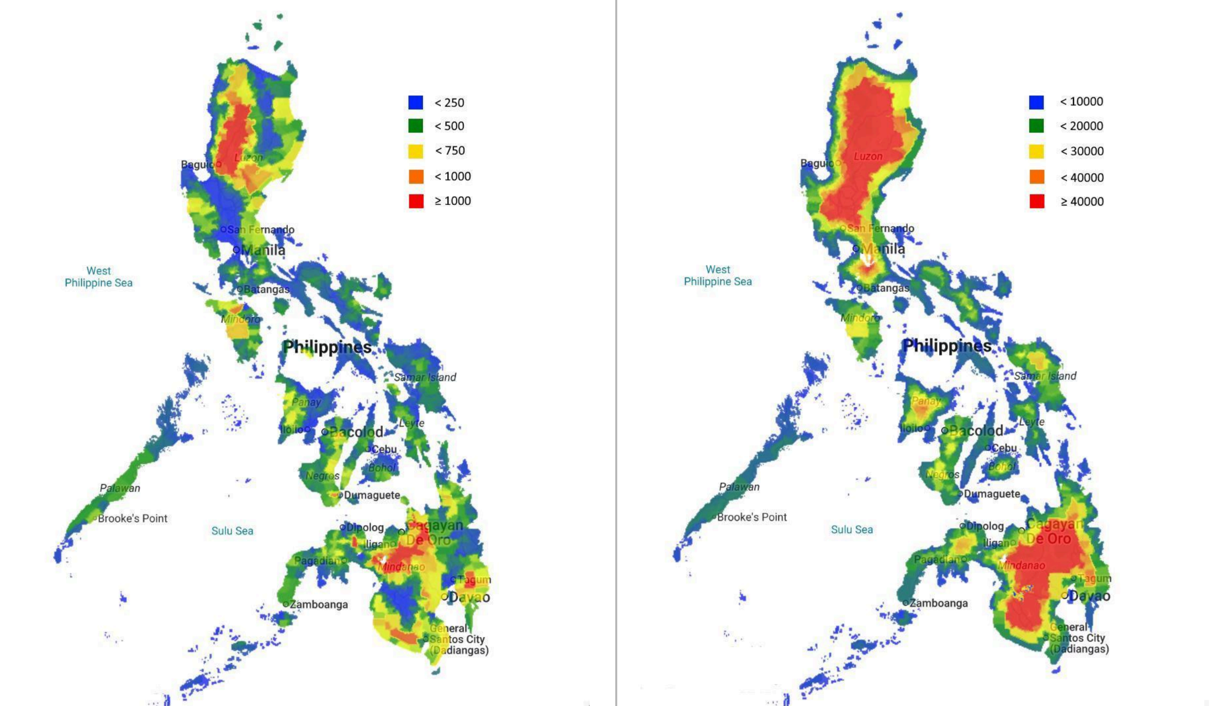
For windspeed, the windspeed (in m/s) for each pixel was calculated using the *u* (eastward) and *v* (northward) wind components, which were obtained from the ERA5-Land Hourly dataset. The maximum windspeed value observed within each municipality was then extracted for the period from November 3rd to November 15th, 2013. For rainfall, total rainfall (in meters) was calculated per pixel over the same period and aggregated at the municipal level by averaging the rainfall across all pixels within each municipality.

Since the ERA5 dataset (rainfall and windspeed) has a resolution of approximately 11 km and covers land areas only, 55 municipalities near the coast lacked direct data. To address this, data from nearby pixels were used to estimate windspeed and rainfall for those municipalities through bilinear resampling, providing a smooth interpolation based on surrounding values.

For elevation and distance to the coast, we aggregated the data by calculating the average value (in meters) for each municipality (*see* Figure 1).



a: windspeed (m/s) **b: Rainfall (cm)**



c: Elevation (m)

d: Distance to Coast (m)

Figure 1: Maps a-d show the four main variables that were used to analyze Typhoon Haiyan's impact on the Philippines in early November 2013. Figure was generated by author from GEE

Census

The Philippine Census, conducted by the Philippine Statistics Authority (PSA), provides detailed demographic data, including population by age, gender, marital status, education, and employment (Philippine Statistics Authority, 2016). For this study, only the population data for each administrative unit from the 2015 Census—the closest census to the time of Typhoon Haiyan—was used.

Social Vulnerability Index

The Social Vulnerability Index (SVI) used in this study was created by a team at the University of Sydney (Lloyd et al., 2022). They aimed to measure social vulnerability at the municipal level across the Philippines. The index incorporates multiple variables such as poverty incidence, unemployment, average household size, population density, literacy, and housing quality. The SVI is standardized, with higher values indicating greater vulnerability. Their findings showed that a one standard deviation increase in the SVI corresponds to a 23.4% increase in typhoon mortality.

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Government Risk Reduction Situation Reports

The National Disaster Risk Reduction and Management Council (NDRRMC) provides detailed situation reports for disasters affecting the Philippines (Disaster Reports, n.d.). These situation reports include timelines of events, numbers of people evacuated and affected, casualty and death counts, damaged houses, cost of damages, infrastructure losses, sector-specific impacts, preparedness actions, and death lists. For this study, impact data from the NDRRMC situation reports were used to assess the damage caused by Typhoon Haiyan, focusing specifically on the number of persons affected. The percentage of persons affected in each municipality was calculated by dividing the reported number of affected persons by the total population from the 2015 census. Due to mismatches between census years and situation report dates, the affected population occasionally exceeds the census population; in such cases, the percentage affected was capped at 100%. Figure 2 visualizes the percentage of persons affected by Typhoon Haiyan in each municipality mapped across the Philippines.

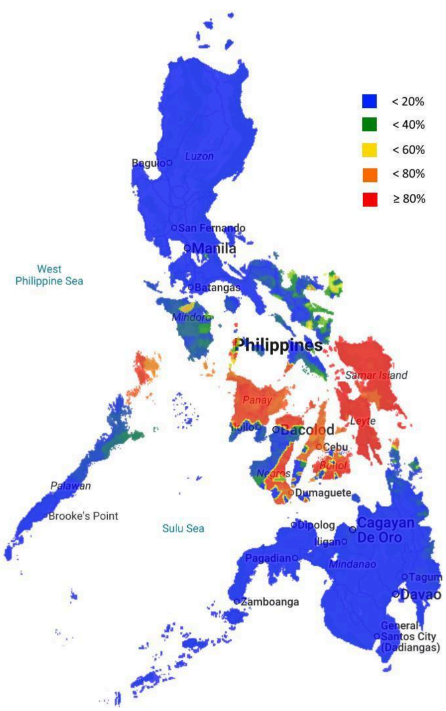

Figure 2: Percentage of persons in each municipality affected by Typhoon Haiyan. Figure was generated by author from GEE

RESULTS

A number of statistical analyses were performed with the percentage of persons affected as the dependent variable, and rainfall, windspeed, distance to coast, elevation, and SVI as independent variables. The results are presented below

Correlation Matrix

A correlation matrix was calculated for the dependent variable and the independent variables (*see* Figure 3). Distance to coast and elevation both negatively correlate with the percentage of persons affected, at -0.33 and -0.16, respectively, reflecting that communities further inland and at higher elevations generally face less severe typhoon damage. In contrast, rainfall and windspeed show strong positive correlations with persons affected, at 0.42 and 0.67, respectively, indicating that stronger winds and heavier rainfall are linked to greater impact. Unexpectedly, the SVI exhibits a negative correlation. A plausible explanation is that the SVI measures potential for poor outcome after typhoon impact rather than the likelihood of being affected by the typhoon. In other words, there is a distinction between vulnerability and exposure, where exposure drives the likelihood of being affected, whereas vulnerability influences the severity.

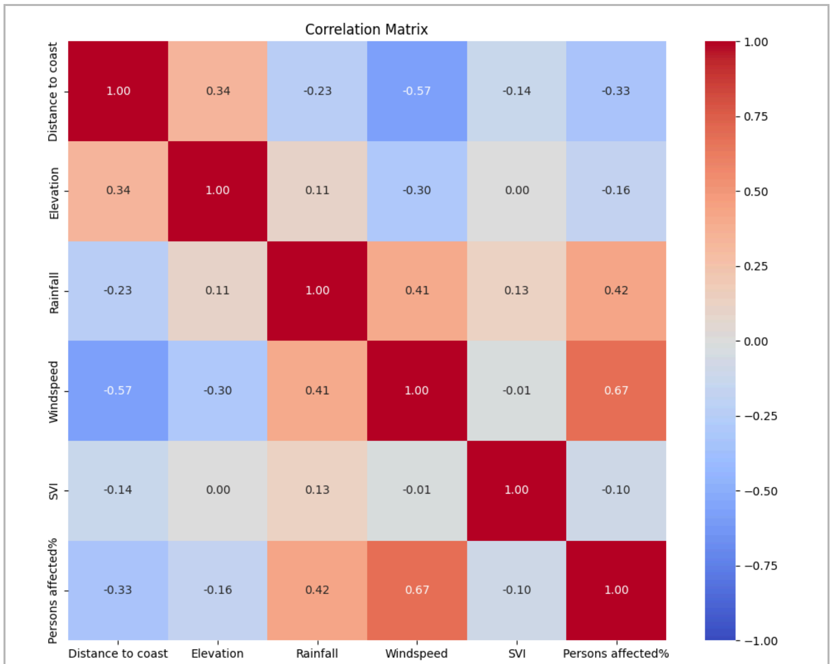

Figure 3: Correlation Matrix of variables

Multiple Linear Regression

After standardizing the dependent variables to have a mean of 0 and a standard deviation of 1, a multiple linear regression was performed. The model yielded an R-squared of 0.497 and an adjusted R-squared of 0.495, indicating that the predictors explain about 49.7% of the variance in the percentage of persons affected. The F-statistic of 264.7 confirms the model is statistically significant. All variables were significant predictors except elevation ($p = 0.425$). Unexpectedly, distance to coast had a positive coefficient, possibly due to its strong correlations with windspeed ($r = -0.57$) and rainfall ($r = -0.23$). Similarly, the SVI had a negative coefficient, which may reflect its role in resilience rather than initial impact. Windspeed and rainfall were identified as the most influential variables, leading to their selection for further analysis using K-means clustering.

Table 1: Multiple Linear Regression Statistics

Parameter	*Coefficient*	*Standard error*	*t-statistic*	*P>|t|*
Constant	0.2646	0.008	33.180	0.000
Distance to coast	0.0232	0.010	2.300	0.022
Elevation	-0.0071	0.009	-0.798	0.425
Rainfall	0.0825	0.009	8.982	0.000
windspeed	0.2545	0.011	23.627	0.000
SVI	-0.0451	0.008	-5.498	0.000

Clustering of municipalities

K-means clustering was applied to capture major differences across municipalities in terms of windspeed and rainfall, while maintaining a simple and interpretable model. An optimal number of clusters was chosen to maximize the silhouette score, which measures both cohesion (how close a point is to others in the same cluster) and separation (how far it is from points in the nearest neighboring cluster). The resulting clusters consist of 396 municipalities in cluster #1, 508 in cluster #2, and 444 in cluster #3. The silhouette score for this model is 0.41, suggesting that the municipalities are reasonably well-separated based on windspeed and rainfall, providing useful groupings for understanding typhoon impacts (*see* Figure 4).

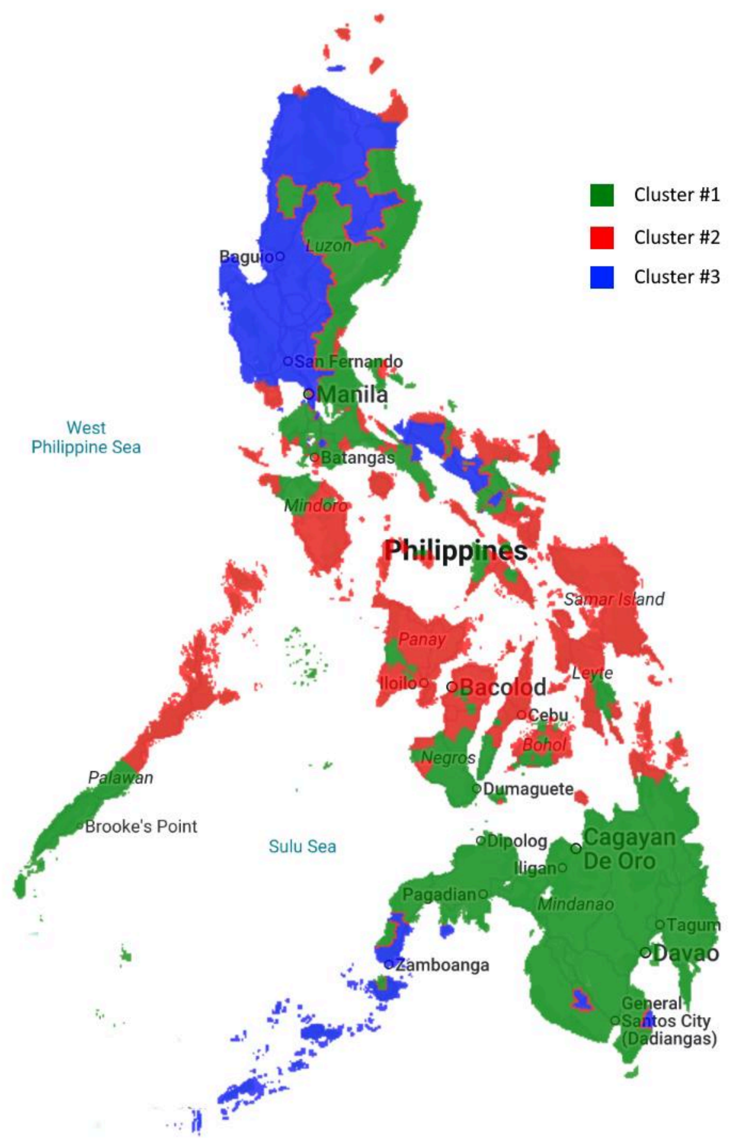

Figure 4: Municipalities of the Philippines by cluster. Figure was generated by author from GEE

Cluster characteristics

Here is a summary of each cluster's characteristics (*also see* Table 2). Cluster #1 includes areas where windspeed is less than or equal to 11.51 m/s and rainfall is greater than 0.10 m, representing regions with high rainfall but low windspeeds. This cluster has the highest average elevation. Cluster #2 represents areas with windspeeds greater than 11.51 m/s, signifying regions experiencing high windspeeds. Cluster #2 is, on average, closest to the coast. Cluster #3 encompasses areas with both low windspeeds (less than or equal to 11.51 m/s) and low rainfall (less than or equal to 0.10 m), denoting low-intensity impact zones.

Clusters #2 and #3 have similar average elevations, which are lower than that of Cluster #1. According to the SVI, Cluster #1 is the most socially vulnerable, followed by Cluster #2, with Cluster #3 being the least vulnerable.

Hazard impact data for each Cluster

Cluster #1 has an average person affected of 10.96%, cluster #2 has an average person affected of 61.27%, and cluster #3 has an average person affected of 0.45%. The table below summarizes the characteristics and impact data for each cluster.

Table 2: Cluster summary

Average	*Cluster #1*	*Cluster #2*	*Cluster #3*
# of municipalities	396	508	444
Elevation(m)	376.58	143.06	198.30
Distance to coast(m)	23763.62	6319.94	23674.76
Rainfall(cm)	0.160	0.173	0.053
windspeed(m/s)	6.196	16.745	6.706
SVI	0.865	-0.224	-0.662
Persons affected	10.96%	61.27%	0.45%

DISCUSSION

The Philippines is highly prone to typhoons with considerable regional variation in impacts. With meteorological and geospatial data at the municipality level, the linear regression model developed explains 49.7% of the variance in the percentage of persons affected by Typhoon Haiyan. The regression result highlights windspeed and rainfall as the dominant factors influencing impact severity.

This study then clustered municipalities into three distinct groups reflecting differences in windspeed and rainfall. Clusters #1 and #3 have very similar windspeeds (around 6.2 m/s vs. 6.7 m/s), but rainfall differs markedly (0.160m vs. 0.053m), leading to a big difference in persons affected (10.96% vs. 0.45%). Similarly, clusters #1 and #2 have comparable rainfall amounts (0.16m vs. 0.17m), but very different windspeeds (6.2 m/s vs. 16.7 m/s), with persons affected vastly different (10.96% vs. 61.27%).

The clustering results further reinforce that rainfall and windspeed have a major impact, responsible for significant changes in the percentage of persons affected.

The clustering results also suggest that the relationship between windspeed, rainfall, and typhoon impacts is complex and nonlinear, not easily captured by simple linear models. For example, the observed roughly 6-fold increase in the percentage of persons affected with just a 10 m/s increase in windspeed between clusters #1 and #2 highlights threshold effects. This aligns with physical principles where kinetic energy of the wind scales with the cube of windspeed (V^3), and pressure with the square of windspeed (V^2), both leading to nonlinear damage escalation as windspeed increases. Earlier studies have found that wind impact typically remains minimal below a specific wind speed threshold but rises rapidly once this threshold is exceeded (Emanuel, 2011; Acosta et al., 2019). This suggests that models could better represent typhoon impacts when incorporating thresholds and/or higher-degree polynomial formulations, rather than relying solely on linear assumptions.

The clustering analysis in this study, specifically the three clusters, can be interpreted as a simple threshold structure. If the windspeed exceeds 11.51 m/s, the municipality is assigned to cluster #2. For those below this threshold, classification is based on a rainfall threshold of 0.10 m: municipalities above this are assigned to cluster #1, and those below to cluster #3. Additionally, for municipalities in cluster #3, the typhoon impact is indeed minimal. Introducing high-degree polynomial models requires advanced quantitative techniques that are beyond the scope of this study.

CONCLUSION

This study investigated Typhoon Haiyan's impact on the Philippines, focusing on the relationship between geospatial and meteorological factors and the percentage of persons affected. Findings reveal that windspeed, rainfall, distance to the coast, and elevation all correlate with the affected population. Windspeed and rainfall show strong positive correlations, while distance to the coast and elevation display weak negative correlations. By utilizing K-means clustering, three distinct clusters of municipalities were identified, corresponding to different impact levels. The cluster, with high windspeed and high rainfall, saw 61% of people affected. The cluster, with higher rainfall but lower windspeed, experienced significantly fewer affected individuals at 11%, while the cluster, with low rainfall and low windspeeds, was almost entirely unaffected by the typhoon. The data also suggests the relationships between these independent variables and the percentage of persons affected are likely nonlinear, indicating that threshold or higher-degree polynomial models may better represent the impact dynamics.

These insights help explain the spatial variability in Typhoon Haiyan's impact and underscore the importance of meteorological and geospatial factors in disaster impact assessments in the Philippines. Earlier studies have shown that global warming is linked to increased typhoon intensity and increased destructive power (*Climate Change Could Double Destructive Power of Asia's Typhoons*, 2022). The findings on windspeed and rainfall in this study corroborate these concerns, indicating that future typhoons are likely to have even greater impacts on residents, and that is a major concern for the Philippines, a country already significantly suffering from the impacts of typhoons.

This study focused on analyzing one typhoon—Typhoon Haiyan—constrained by the substantial effort required to clean and match datasets, particularly manually collecting municipal-level data from the situation reports. Further research could extend this analysis to include other major typhoons, enabling the development of improved predictive models and the identification of broader patterns of typhoon impacts. Additionally, this study employed three clusters based on two variables (windspeed and rainfall); future work could explore using more clusters, incorporating additional variables, and introducing higher-degree polynomial formulas to better capture the complexity of typhoon impacts.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to the project supervisor, Dr. Magaly Koch (Research Associate Professor at the Boston University Institute for Global Sustainability), and project advisor, Sultan Mussakhan (Ph.D. candidate in Biological Sciences at Brock University, Canada), for their invaluable guidance and inspiration throughout this research.

REFERENCES

2024 typhoon season WFP Philippines response report. (2025). In *World Food Programme* (p. 4). https://www.wfp.org/publications/2024-typhoon-season-wfp-philippines-response-report

Acosta, P. A., Skoufias, E., Kawasoe, Y., & Strobl, E. (2019). Identifying the vulnerable to poverty from natural disasters : The case of typhoons in the Philippines. In *World Bank Group*. World Bank Group. http://documents.worldbank.org/curated/en/326941558453867995

Becek, K., Koppe, W., & Kutoğlu, Ş. (2016). Evaluation of vertical accuracy of the WorldDEMTM using the runway method. Remote Sensing, 8(11), 934. https://doi.org/10.3390/rs8110934

Chaivutitorn, T., Tanasakcharoen, T., Leelawat, N., Tang, J., Caro, C. V. C., Lagmay, A. M. F. A., Suppasri, A., Bricker, J. D., Roeber, V., Yi, C. J., & Imamura, F. (2020). Statistical analysis of building damage from the 2013 super typhoon Haiyan and its storm surge in the Philippines. *Journal of Disaster Research*, *15*(7), 822–832. https://doi.org/10.20965/jdr.2020.p0822

Cinco, T. A., de Guzman, R. G., Ortiz, A. M. D., Delfino, R. J. P., Lasco, R. D., Hilario, F. D., Juanillo, E. L., Barba, R., & Ares, E. D. (2016). Observed trends and impacts of tropical cyclones in the Philippines. *International Journal of Climatology*, *36*(14), 4638–4650. https://doi.org/10.1002/joc.4659

Climate change could double destructive power of Asia's typhoons. (2022, April). CUHK | Office of Academic Links; The Chinese University of Hong Kong. https://www.oal.cuhk.edu.hk/cuhkenews_202204_asia_typhoons/

Damages due to natural extreme events and disasters amounted to PhP 463 billion. (2020, October 28). Philippine Statistics Authority. https://psa.gov.ph/statistics/environment/peenra/node/163321

Disaster reports. (n.d.). National Disaster Risk Reduction and Management Council. Retrieved September 21, 2025, from https://ndrrmc.gov.ph/disaster-reports.html

Emanuel, K. (2011). Global warming effects on U.S. hurricane damage. *Weather, Climate, and Society*, *3*(4), 261–268. https://doi.org/10.1175/wcas-d-11-00007.1

Google Earth Engine. (2019). Google Earth Engine; Google. https://earthengine.google.com/

Kim, J.-M., Son, K., Yoo, Y., Lee, D., & Kim, D. Y. (2018). Identifying risk indicators of building damage due to typhoons: Focusing on cases of south korea. *Sustainability*, *10*(11), 3947–3947. https://doi.org/10.3390/su10113947

Kim, J.-M., Son, K., Yum, S.-G., Ahn, S., & Ferreira, T. (2020). Typhoon vulnerability analysis in South Korea utilizing damage record of Typhoon Maemi. *Advances in Civil Engineering*, *2020*, 1–10. https://doi.org/10.1155/2020/8885916

Lagmay, A. M. F., Agaton, R. P., Bahala, M. A. C., Briones, J. B. L. T., Cabacaba, K. M. C., Caro, C. V. C., Dasallas, L. L., Gonzalo, L. A. L., Ladiero, C. N., Lapidez, J. P., Mungcal, M. T. F., Puno, J. V. R., Ramos, M. M. A. C., Santiago, J., Suarez, J. K., & Tablazon, J. P. (2015). Devastating storm surges of Typhoon Haiyan. International Journal of Disaster Risk Reduction, 11, 1–12. https://doi.org/10.1016/j.ijdrr.2014.10.006

Li, Y., Wu, J., Tang, R., Wu, K., Nie, J., Shi, P., Li, N., & Liu, L. (2022). Vulnerability to typhoons: A comparison of consequence and driving factors between Typhoon Hato (2017) and Typhoon Mangkhut (2018). *Science of the Total Environment*, *838*, 156476–156476. https://doi.org/10.1016/j.scitotenv.2022.156476

Lloyd, S., Gray, J., Healey, S., & Opdyke, A. (2022). Social vulnerability to natural hazards in the Philippines. *International Journal of Disaster Risk Reduction*, *79*, 103103. https://doi.org/10.1016/j.ijdrr.2022.103103

McCallum, B. E., Wicklein, S. M., Reiser, R. G., Busciolano, R. J., Morrison, J., Verdi, R. J., Painter, J. A., Frantz, E. R., & Gotvald, A. J. (2013). Monitoring storm tide and flooding from Hurricane Sandy along the Atlantic coast of the United States, October 2012. In U.S. Geological Survey (pp. 1–42). United States Department of the Interior. https://doi.org/10.3133/ofr20131043

Muñoz Sabater, J. (2019). ERA5-Land monthly averaged data from 1950 to present. Copernicus Climate Change Service. Climate Data Store. https://doi.org/10.24381/cds.68d2bb30

Philippine Statistics Authority. (2016, May 19). Highlights of the Philippine population 2015 census of population. Philippine Statistics Authority; Republic of the Philippines. https://psa.gov.ph/content/highlights-philippine-population-2015-census-population

Ransom, C. N. (2013). Hurricane Sandy science plan: New York. In U.S. Geological Survey. U.S. Department of the Interior. https://doi.org/10.3133/fs20133089

Santos, G. D. C. (2021). 2020 tropical cyclones in the Philippines: a review. Tropical Cyclone Research and Review, 10(3), 191–199. https://doi.org/10.1016/j.tcrr.2021.09.003

Tam, F. (2017, January). *The science behind extreme weather, sea level rise and storm surges*. Sustainable Campus; The Chinese University of Hong Kong. https://www.iso.cuhk.edu.hk/english/publications/sustainable-campus/article.aspx?articleid=64656

Typhoon Haiyan (Yolanda). (2023). World Health Organization. https://www.who.int/westernpacific/emergencies/typhoon-haiyan-%28yolanda%29

WMO. (2022, December 16). *Tropical cyclone*. World Meteorological Organization. https://wmo.int/topics/tropical-cyclone

Ye, M., Wu, J., Liu, W., He, X., & Wang, C. (2020). Dependence of tropical cyclone damage on maximum wind speed and socioeconomic factors. *Environmental Research Letters*, *15*(9), 094061. https://doi.org/10.1088/1748-9326/ab9be2