A spatial cluster analysis of Philippine municipalities for disaster risk reduction and management

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ABSTRACT

The Philippines encounters an overwhelming number of natural disasters annually, including earthquakes, due to its geographical location. The government has a vested interest in developing efforts to improve its preparedness and capacities across all levels. We use a spatial cluster analysis to create a typology of risk levels of 1,588 municipalities when it comes to earthquakes. We scraped publicly available disaster data from multiple sources and reduced the number of dimensions through truncated SVD. We used *k*-means clustering to surface four overarching clusters and describe them in this paper. These clusters share vulnerability profiles and can thus be valuable for the government in preparing for disaster risk reduction and management (DRRM).

KEYWORDS

Natural disasters; Earthquakes; Cluster analysis; Disaster risk reduction; Disaster management

INTRODUCTION

In 2021, the Philippines ranked the 8th most affected country out of 181 in the World Risk Index. Measuring exposure, vulnerability, and susceptibility to hazard events, it also quantifies a country's coping and adaptive capacities to respond proactively to weather events when they occur (Aleksandrova et al., 2011). This is reflective of the inherent risks associated with island states around the Pacific Rim due to their geographical location. The Philippines is obviously no exception: Typhoons, for instance, average around 20 times and sporadic eruptions from its 220 volcanoes annually, notwithstanding major fault lines that traverse the entire archipelago (Jha et al., 2018). Trends show that typhoons entering the Philippine Area of Responsibility are getting fewer but are growing more extreme (Cinco et al., 2016).

Disaster risk reduction and management (DRRM) has thus been a priority of the government since the 1970's. The *National Disaster Risk Reduction and Management Council* (NDRRMC) is the mandated body to respond to the needs of a changing climate: It was through the 2010 DRRM Act that a calamity fund was instituted, along with a focus on pre-disaster risk management from public announcements to public education (Brower et al., 2014).

Our objective in this paper is to identify the overarching clusters of Philippine municipalities based on publicly available geospatial and disaster data. The government through the NDRRMC must manage between competing priorities when disaster strikes. Decision-makers thus need to be proactive in reducing and managing risks related to disasters: "Which municipalities are the most at-risk when a disaster strikes?" Answering this question can be challenging due to the varying levels of data quality from the overwhelming number of municipalities in the country. We propose a clustering approach in grouping the 1,488 municipalities in the country to develop a risk register that can aid DRRM efforts of the national government.

There have been previous efforts to quantify disaster data and create indices for DRRM. A majority of these has either been limited to a specific area or domain. One study created a localized Disaster Risk Management Index (DRM) using survey data, to evaluate preparedness of each municipality to hydrometeorological hazards (i.e., strong winds, rains, floods, landslides, and big waves) (Ravago et al., 2020). We build on their efforts and contribute to the literature by focusing on earthquakes and using a machine learning method to cluster municipalities based on the level of risk.

METHODOLOGY

Data sources

We used publicly available data from the API of the United States Geological Survey (USGS) to scrape all earthquake data, with magnitudes 4 and above, recorded from the Philippines in GeoJSON between years 2010 and 2021 (U.S. Geological Survey, n.d.). Because USGS API data only provides the magnitude of each recorded event, earthquakes were manually categorized into light, moderate, strong, and major following industry standards. As seen in Table 1, each category has its own estimated reach in terms of the radius of the impact of an earthquake depending on the recorded magnitude. For example, a buffer of 20 km was used for the moderate magnitude. While the actual extent may vary, these estimates are based on literature we used as reference.

Table 1. Categories and Kilometer Reach per Earthquake Category

Category	Magnitude	Buffer
Light	4 – 4.9	5 km
Moderate	5 – 5.9	20 km
Strong	6 – 6.9	100 km
Major	7 – 7.9	200 km

We then used a database of active faults globally maintained by the GEM Foundation (Styron & Pagani, 2020). A total of 116 active fault lines are available for the Philippines. Only geometric features of fault lines were included; other seismological features were excluded. Both the USGS data and GEM data were combined with the spatial data provided by the GADM Database that provides spatial data on countries (GADM, n.d.). We combined this with information on the amenity, hospital, and population counts and the municipality income figures. Prior to merging and saving as a single SHP file to ensure compatibility during visualization and analysis, the data was cleaned by converting appropriate columns to float whenever applicable.

Exploratory geospatial analysis

We overlaid the three datasets on top of each other to reveal high-level insights as seen in Figure 1. As expected, most earthquakes happen near the active fault lines; these were more frequent in the southern part of the country and were less likely to be observed in the north. Light and moderate earthquakes greatly outnumber major ones. Major earthquakes are rare, but they were always near, but never in, shorelines or actual land areas.

Dimensionality reduction and clustering

We plotted the correlation coefficients to see which variables are highly correlated (Figure 2). We then use truncated SVD to reduce dimensions as data is sparse. Using the Inertia (Figure 3) and Calinski-Harabasz (Figure 4) plots as our internal validation criteria, we used k = 4 for k-means clustering (Figure 5). Labelling followed an analysis of each cluster's municipalities. These are summarized in the next section.

RESULTS AND DISCUSSION

We identified four clusters of Philippine municipalities, using *frequency* and *severity* to describe their vulnerability profiles. *Frequency* indicates the number of past earthquake count data. While the authors recognize that this is not indicative of future earthquakes, mean magnitudes that a municipality experience may inform of their capacity in disaster management. *Severity* indicates the possible extent of damage that an earthquake results to given the number of amenities, income, and population density.

Figure 10 shows the distribution of the clusters in relation to the features we looked at in clustering the municipalities.

Table 2. Summary of Clusters

Cluster	Frequency	Severity
A	Low	Low
B	High	High
C	Low	High
D	High	Low

Cluster A: Low Frequency & Low Severity

Cluster A are municipalities that have a low earthquake count but when hit, mean magnitudes are highest among all clusters. They have the lowest population density and low amenity counts. These are the municipalities colored in black in Figure 6. In Luzon, this includes most of the Ilocos Region, and parts of Zambales (Figure 7).

In Visayas, a large part of Samar and Leyte are included in this cluster (Figure 8). These directly face the Pacific Ocean and the Ring of Fire.

In Mindanao, Zamboanga, Marawi, and Cotabato cities are included (Figure 9), which are some of the city centers in this part of the island.

Since this cluster have low population density and low amenity counts, resources may not be readily available in these areas, and so very prompt attention is needed to ensure proactive response.

Cluster B: High Frequency & High Severity

Cluster B are municipalities with the highest amenity count and a high earthquake count. Mean magnitudes are in the middle. These are the municipalities colored in violet in Figure 6.

The lone violet area in the north is Apayao (Figure 7), as part of the Cordillera Administrative Region, of which location is mostly mountainous and can be hard to reach. At the lower left of the Luzon Island are some areas in violet: These are in Batangas, which have much higher amenity counts.

In Visayas, we see that most of Bohol are in this cluster (Figure 8). They differ starkly from Cebu, which is right beside it; this could possibly be due to the existing Bohol Fault System in the area. A newly found North Bohol Fault followed the 2013 Bohol earthquake. It was the deadliest earthquake in the Philippines after 23 years; 3 weeks later after it occurred, Typhoon Haiyan disrupted its neighboring islands of Samar and Leyte (Matus, 2013).

Southern Mindanao and CARAGA round up this cluster (Figure 9); the former is near the Sulu Trench in the Sulu Sea and the Cotabato Trench. This region is characterized by moderate to high seismicity according to PHIVOLCS.

Cluster C: Low Frequency & High Severity

Cluster C comprises of highly populated municipalities with the lowest earthquake count. Mean magnitudes are also low. These are the municipalities colored in orange in Figure 6.

A large part of the Luzon Island falls under this cluster (Figure 7), even if some of the active fault lines traverse this part of the country. It appears that earthquakes occur more often at or near bodies of water. However, it is also important to note that most of the active faults in Luzon are in this area.

Moving to Visayas, we see the difference between Clusters C (orange, in Figure 8) and A (black, in Figure 8); as mentioned above, the latter mostly faces the Pacific Ocean. The islands of Negros, Iloilo, and Cebu fall largely under Cluster.

Cagayan de Oro, Camiguin, and Butuan are some of the areas that fall under Cluster C (Figure 9). Clearly, they may be near bodies of water, but they have a more limited exposure to the oceans surrounding the Mindanao Island.

Cluster D: High Frequency & Low Severity

These municipalities experience the most earthquakes, but not all are damaging. They are moderately populated with the lowest amenity counts. These are colored in light brown in Figures 6 and 9. Most of Davao del Sur, and some municipalities in Maguindanao, North Cotabato, and Sultan Kudarat were included in this cluster, which, incidentally, also recorded high poverty incidence in the region.

CONCLUSION

In this paper, we have demonstrated the groups that surfaced from *k*-means clustering. These clusters can help the government in being proactive when it comes to disaster risk reduction and management. If it can identify areas that require the most attention, it can focus its efforts on these locations to build the capacity of municipalities to respond when hazard events happen. Second, civil society organizations—both non-profit and private sector organizations—can use it to narrow down or target segments. For example, some areas can be purposely targeted to provide more relevant insurance products. Finally, a specific use case is that the clusters can help the logistics industry in selecting ideal areas for its warehouses or during delivery. In times of disaster, it can repurpose its warehouses for distribution of goods and services to help its customers and the government as they recover from disaster.

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FIGURES

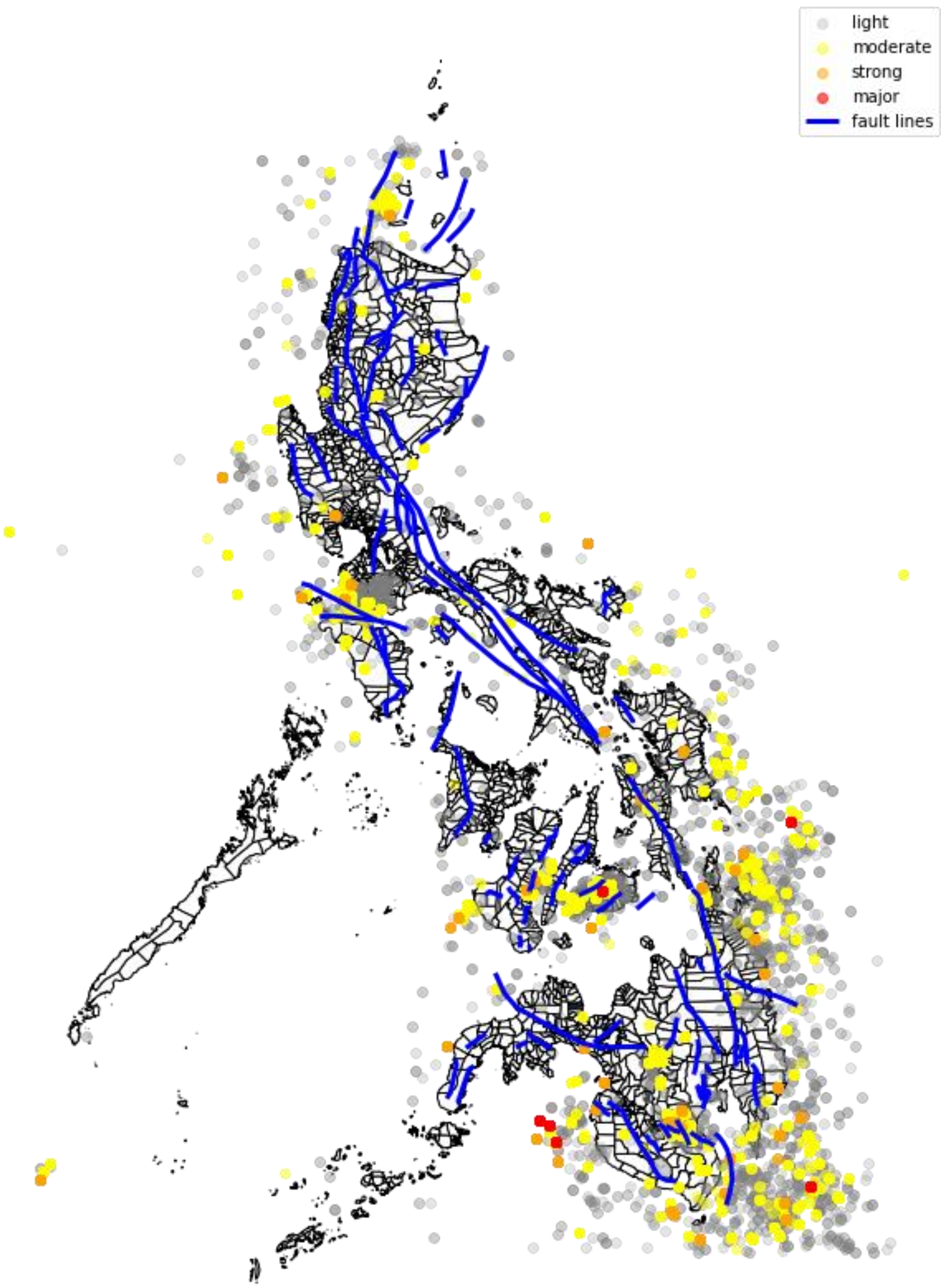

Figure 1. Earthquakes with Magnitude 4 and above and active fault lines in the Philippines, 2010-2021

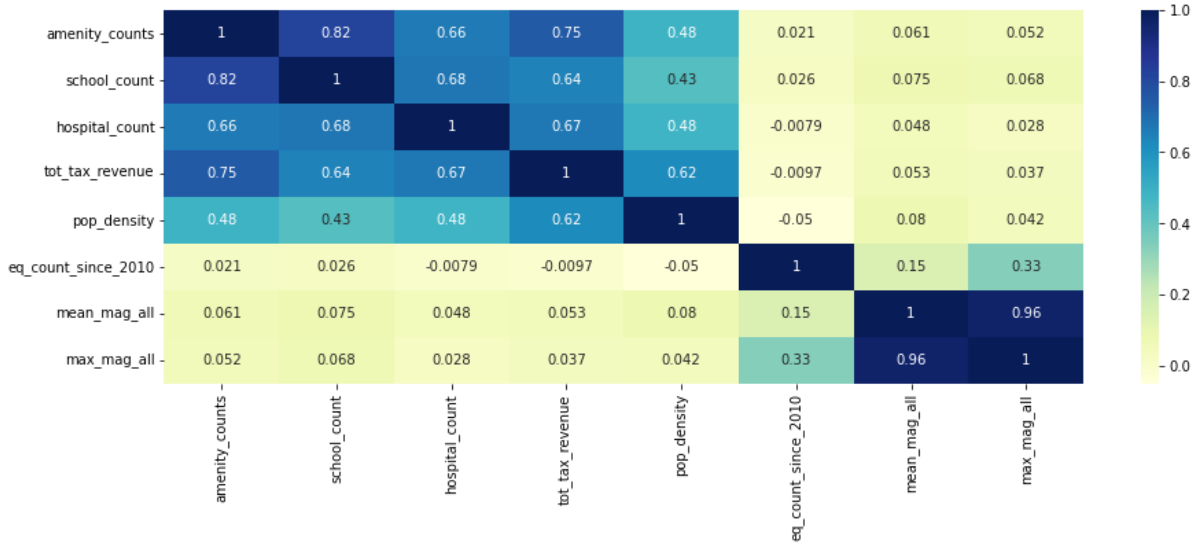

Figure 2. Correlation coefficients of all variables

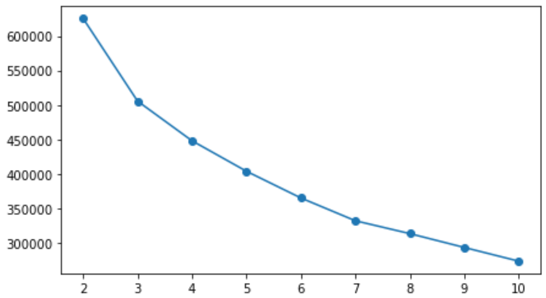

Figure 3. Inertia Plot

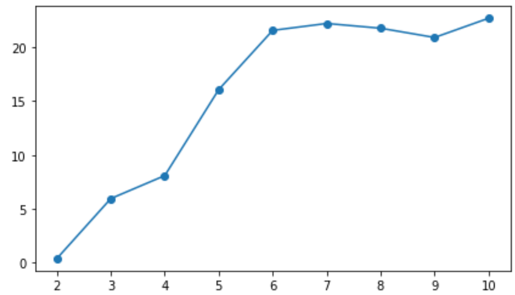

Figure 4. Calinski-Harabasz Plot

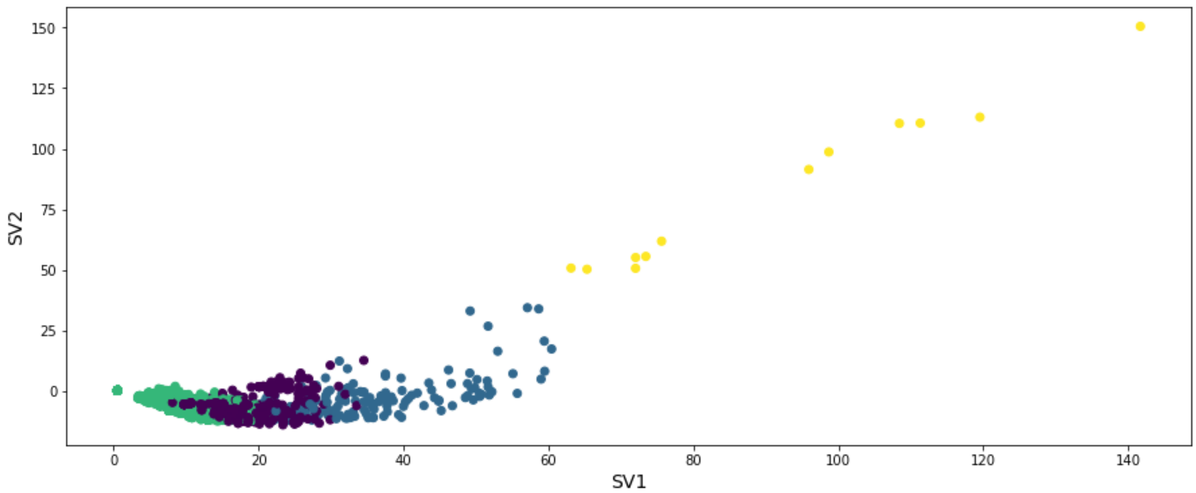

Figure 5. *k*-means Clustering

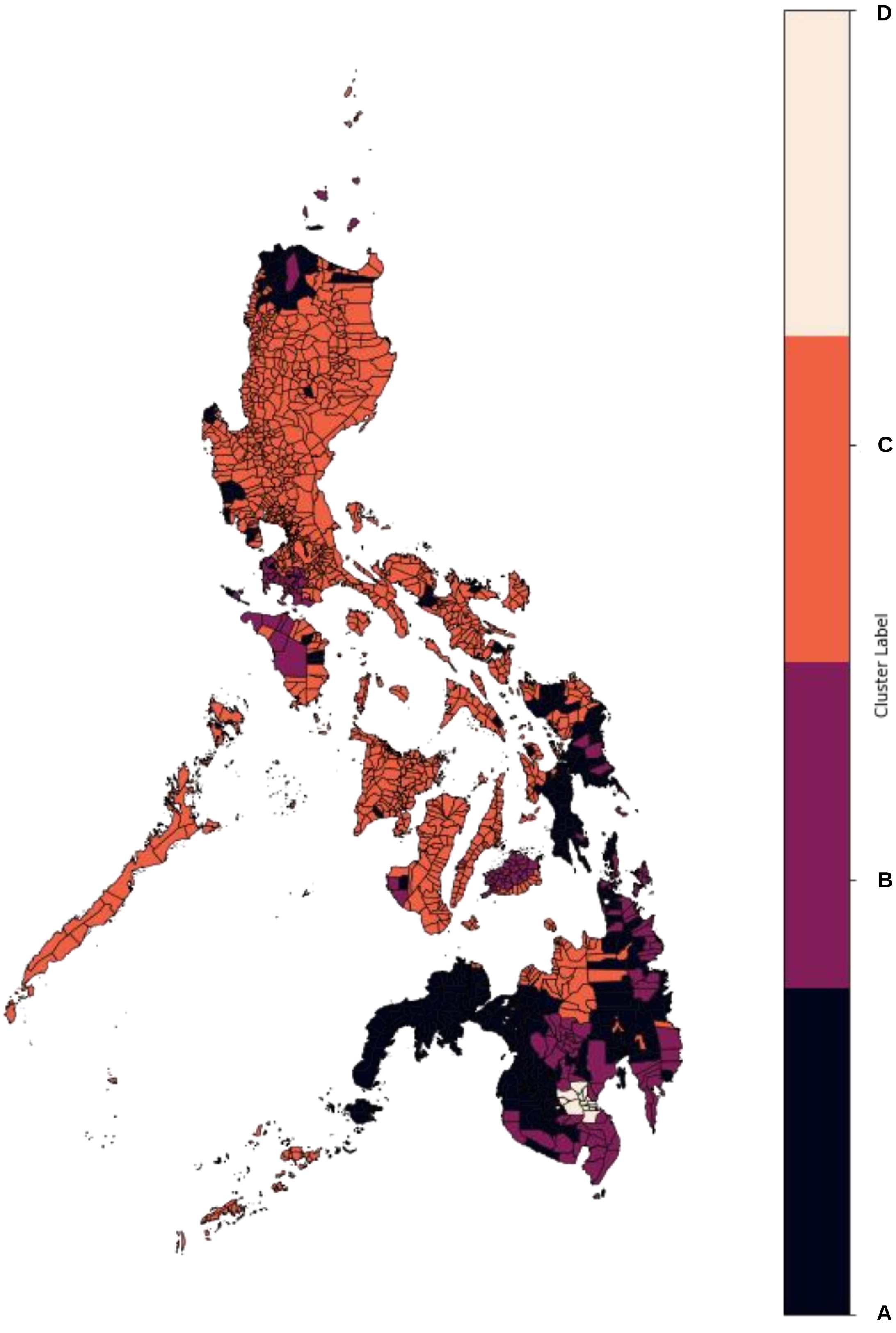

Figure 6. Clustering results of Philippine municipalities

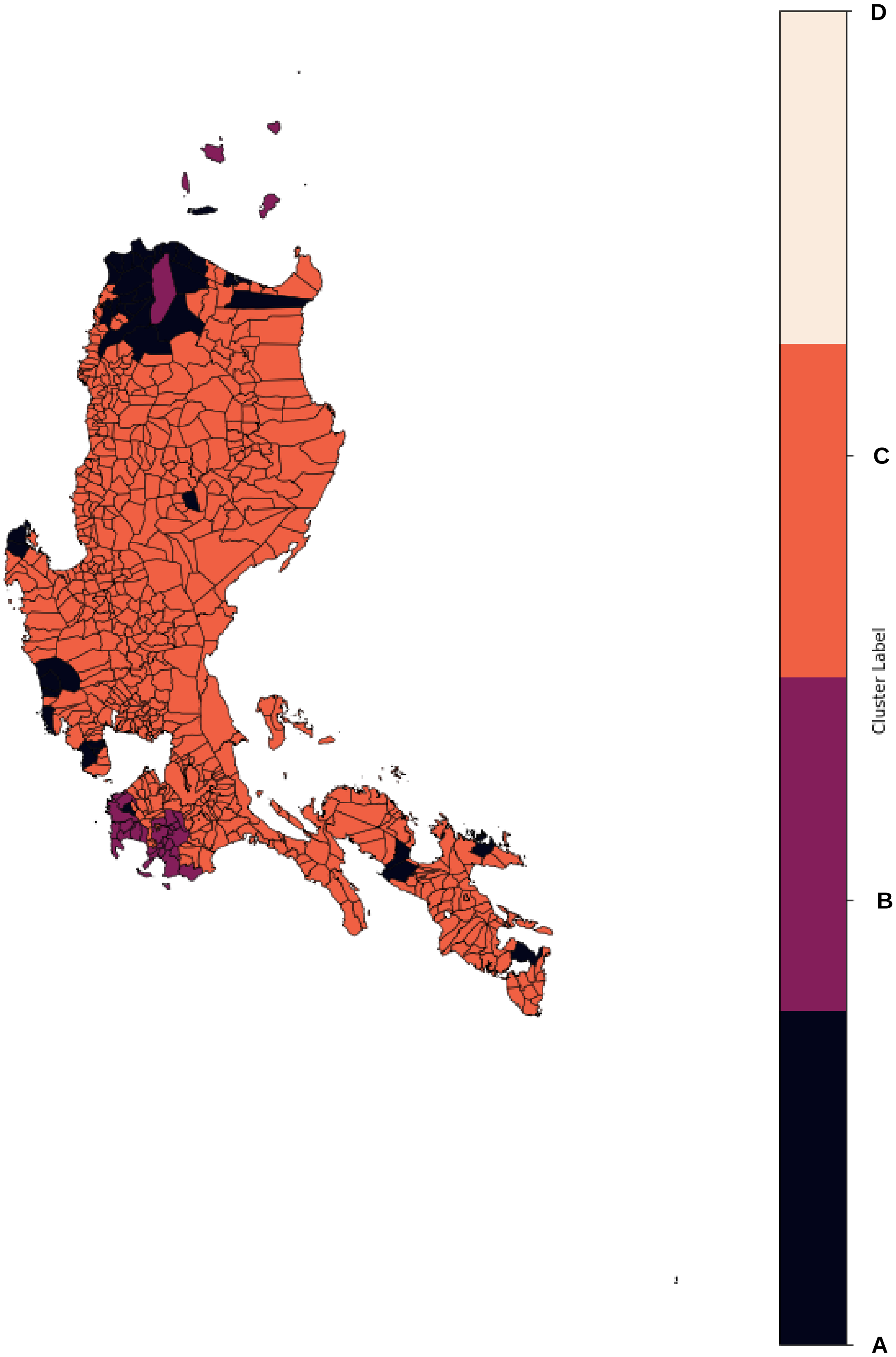

Figure 7. Clustering results of Luzon municipalities

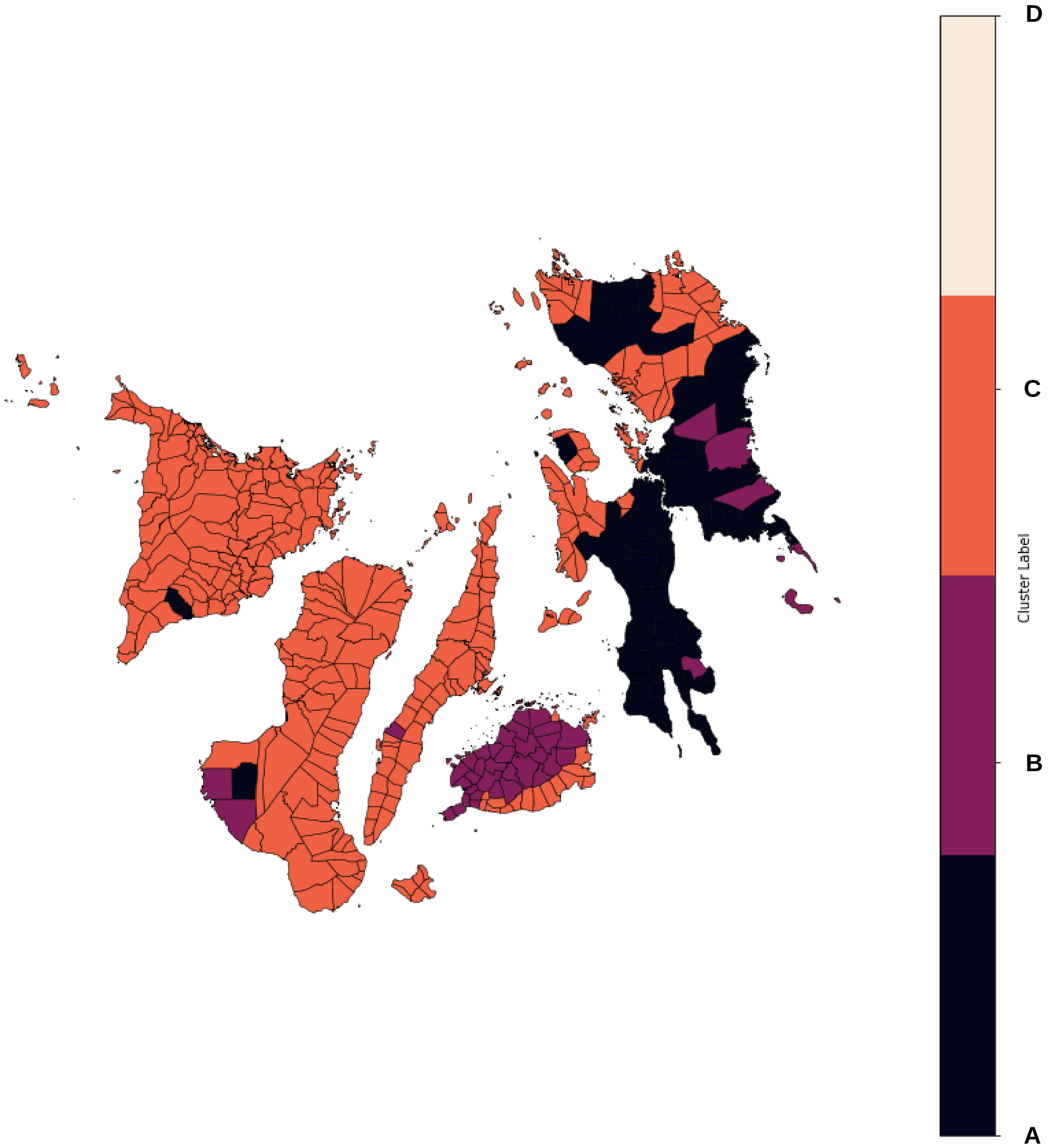

Figure 8. Clustering results of Visayan municipalities

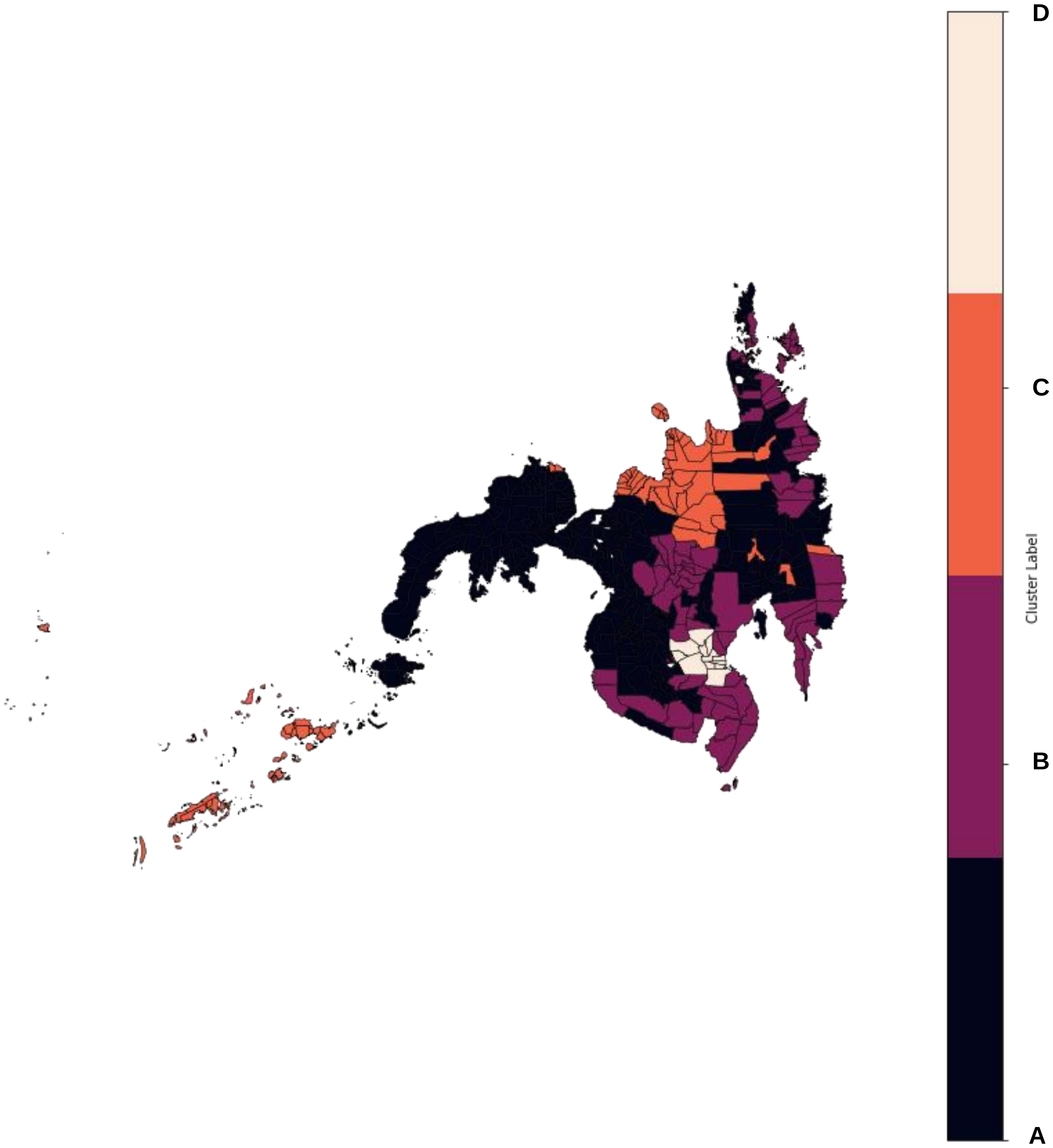

Figure 9. Clustering results of Mindanaoan municipalities

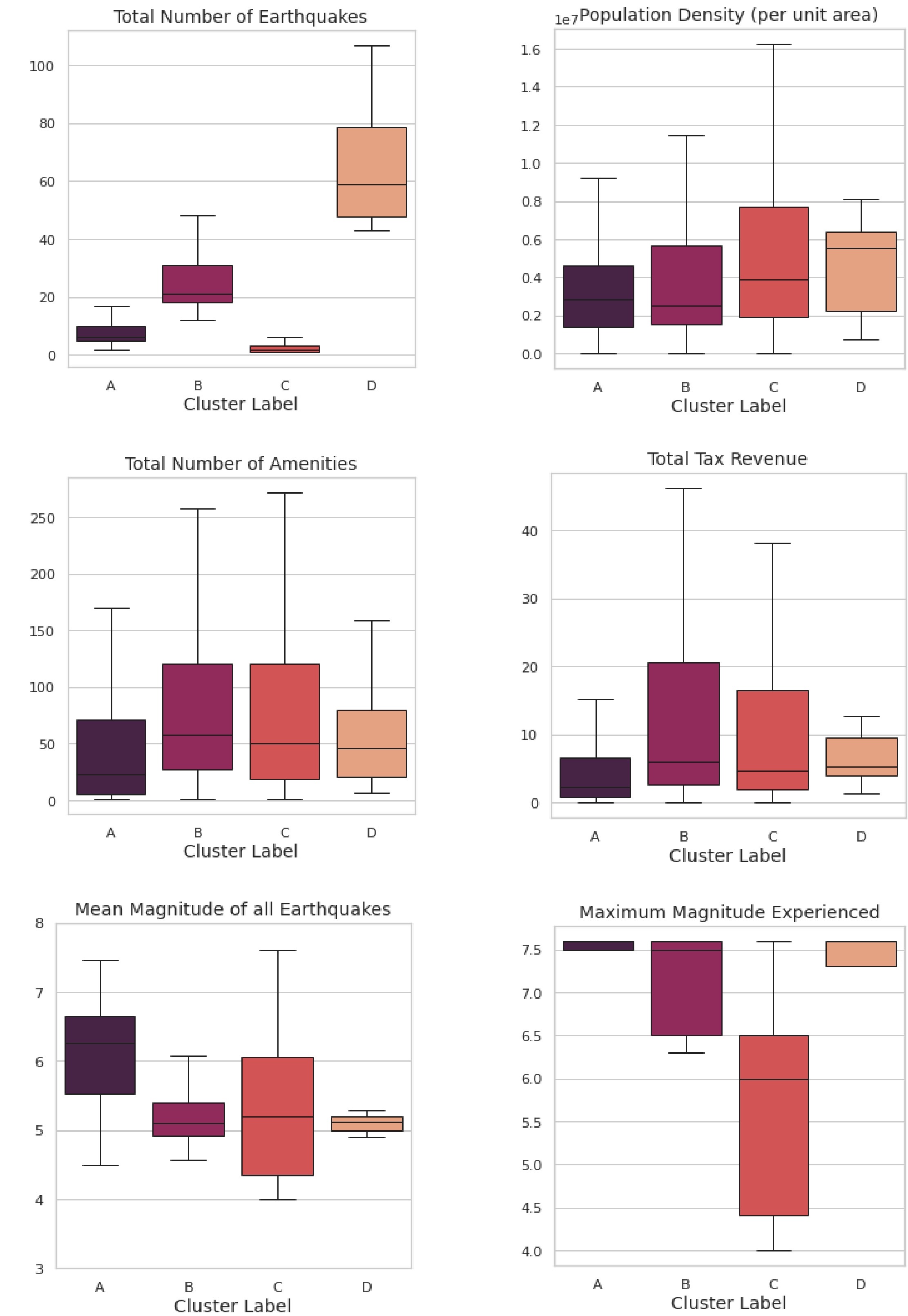

Figure 10. Boxplots showing cluster characteristics