COVID-19 susceptibility mapping: a case study for Marinduque Island, Philippines

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Abstract
Small islands are highly susceptible to infectious disease outbreak and other health emergencies because of their remoteness, small physical size, and poorly developed infrastructure. These are true in the case of Marinduque, an island province around 200 km south of the National Capital Region (NCR), which is the “epidemiological epicenter” of the COVID-19 pandemic in the Philippines. This study utilized GIS and Principal Component Analysis (PCA) using demographic, socioeconomic, and geographic indicators to map susceptibility of different villages in the island province of Marinduque, the Philippines. Based on the results, the northwestern and northeastern portion of Marinduque has a higher susceptibility score. Also, villages in the town centers have relatively high susceptibility scores compared to other villages in each municipality.

Keywords COVID-19 · Island province · PCA · GIS

1 Introduction COVID-19 · Island province · PCA · GIS

Small islands are small landmasses surrounded by sea or ocean that are frequently prone to either geological or hydrological disasters [1–4]. These small islands are also most likely vulnerable to climate change and other natural disasters due to their remoteness, small physical size, limited natural resources, sensitive economies, high population densities and growth rates, limited financial and human resources, and poorly developed infrastructure [1]. These characteristics also curb their capacity to prepare for and respond to acute environmental and health emergencies, making them susceptible to infectious disease outbreaks [5, 6].

Based on the data from the World Health Organization webpage [7], there are more than 47 million confirmed cases of COVID-19 across the globe. In the Philippines, at the moment, there are more than 388 thousand confirmed cases since the first suspected case in January and confirmed local transmission last March 2020 [8, 9]. Several measures were implemented by the Philippine government to respond to the COVID-19 pandemic including enhanced community quarantine or lockdown. The lockdown required social distancing and home isolation [10, 11]. Class suspension in all school levels and offices adapted work-from-home arrangements [10, 11]. Mobility outside the residence is limited to buying basic necessities within the non-curfew hours of 5 am to 7 pm [10]. Only transportation for essential service are allowed while other lands, sea, and air transportation are banned [11]. However, after the lockdown, individuals working in the National Capital Region (NCR) or the “epidemiological epicenter” of the COVID-19 pandemic in the Philippines [12], started traveling back to their home provinces, causing sporadic cases of COVID-19 in the countryside.

Marinduque is an island province in the heart of the Philippine archipelago [13, 14]. It is 3 h away by sea (via roll-on roll-off boat) from mainland Luzon. The province is mostly mountainous with rolling to steep slopes in the inner portion and flat coastal areas in the other region [15–17]. Marinduque is consist of 218 villages that are within 6 municipalities. Farming and fishing are the primary sources of livelihood in the province [4, 16]. Poverty and child malnutrition are prevalent in the Marinduque [13, 16, 18]. Recently, the province has already recorded positive COVID-19 cases from travelers from mainland Luzon.
Susceptibility mapping is an approach that is common in landslide studies [19]. It involves the generation of landslide susceptible areas based on maps of different factors that influence landslide occurrence [19, 20]. There are three (3) types of approaches common to susceptibility assessment, namely: (1) knowledge-based; (2) physical; and, (3) data-based [21–23]. GIS maps and tables are the final results of susceptibility assessment [24–26]. In the case of COVID-19, Sarkar [27] used a knowledge-based approach (i.e. multi-criteria) to assess the susceptibility of districts in Bangladesh based on different physical, socio-economic, and demographic variables.

The principal component analysis is a distance-based multivariate statistical technique used in reducing the dimensionality of a large dataset with the purpose of filtering, developing predictive models, or constructing a composite indicator that explains the maximum variation in the original dataset [28–30]. Using orthogonal transformation, PCA transforms the dataset of possibly correlated variables into a combination of uncorrelated principal components (PCs) based on the covariance or correlation matrix [31–33]. Syms [30] provides a detailed discussion of PCA. In social sciences, PCA is commonly used to develop a composite index for development [31, 34], health [35], quality of life [36], and social vulnerability [29, 37–39].

This paper aims to assess the susceptibility of different villages in the island province of Marinduque, Philippines using GIS and PCA. It aims to help the local government and health agencies in the province to identify areas or villages that are highly susceptible to COVID-19 outbreak based on their demographic, socio-economic, and geographic characteristics. Identification of highly susceptible areas can help local authorities to develop measures to prevent further COVID disease outbreak in the province.

2 Methodology

2.1 Data

Most of the data for the province of Marinduque (Fig. 1) used in this study were from the Provincial Planning Development Office (PPDO) of the province, including the socio-economic and demographic variables from the 2015 Community Based Monitoring System (CBMS) (Table 1). The PPDO also provided the road network map of the province. The geographic variables such as average distances from the main highway, health facilities, ports, and town centers were calculated using GIS. The locations of health facilities, ports, and town centers were from Salvacion [16].

2.2 Development of susceptibility index

All variables in Table 1 were normalized before PCA [40]. Then, a village-level COVID 19 susceptibility index for Marinduque was calculated using PCA. The index is the summation of factor loading from the principal components with eigenvalue > 1 [37, 41, 42]. The index value was further normalized using min-max transformation (Eq. 1) [43].

\[
NV = \frac{X_i - X_{min}}{X_{max} - X_{min}}
\]

where \( NV \) is the normalized value.

\( X_i \) is the actual value of the index.

\( X_{min} \) is the minimum value of the index.

\( X_{max} \) is the minimum value of the index.

3 Results and Discussion

3.1 Demographic indicators

Based on the 2015 CBMS of Marinduque, most of the densely populated areas were villages near the town centers of the province (Fig. 2a). On average, the population density (people/km²) of a village in Marinduque is around 859, with a minimum of 26 and a maximum of 14,183. The proportion of child population ranges from 3.31 to 24.71%, with a mean of 11.41%. Most villages with a high proportion of children in the province inner portion of the province...
The proportion of the population age 65 and above ranged from 2.16 to 15.74%, with a mean of 7.37%. Villages with a high proportion of the population age 65 and above are mostly in the north to the eastern portion of Marinduque (Fig. 2c). The proportion of male population per village in Marinduque ranges from 38.91 to 66.80%, with a mean of 54.34%. Higher proportions of the male population were mostly in the inner and southern portion of the province (Fig. 2d). Table 2 summarizes the descriptive statistics of demographic indicators for COVID susceptibility of Marinduque.

### 3.2 Socio-economic indicators

Figure 3 shows the map of different socio-economic indicators of Marinduque, Philippines. Most of the villages with a high proportion of informal settlers are in the interior portion of the province (Fig. 3a). The percentage of informal settlers in Marinduque ranges from 0 to 50.29% and a mean of 2.81% per village. Higher proportions of the population without access to safe water are in the mountainous and island villages of the province (Fig. 3b). On average, around 3.76% of the population has no access to safe water and ranges from 0 to 25.20% per village. The mean village level unemployment rate is around 8.42% and ranges from 0 to 52.76%. There is a higher unemployment rate in the southwestern part of Marinduque (Fig. 3c). The poverty incidence in the province ranges from 3.30 to 96.20%, and a

### Table 1 Variables for constructing COVID-19 susceptibility index

| Variable | Description | Increase (+) or Decrease (-) COVID-19 Susceptibility | Reference | Source |
|----------|-------------|----------------------------------------------------|-----------|--------|
| PopDen   | Population Density (people/ km²) | + | 29,45,46 | CBMS    |
| %Children | Proportion of the population that are 0–5 years old | + | 29 | CBMS    |
| %Age65   | Proportion of the population that are 65 and above years old | + | 29,47–50 | CBMS    |
| %Male    | Proportion of male population | + | 49 | CBMS    |

### Table 2 Descriptive statistics of demographic indicators for COVID-19 in Marinduque, Philippines

| Variable | Minimum | Mean  | Maximum | Standard Deviation |
|----------|---------|-------|---------|--------------------|
| PopDen   | 26      | 859   | 14,183  | 1691               |
| %Children | 3.31    | 11.41 | 24.70   | 3.02               |
| %Age65   | 2.16    | 7.37  | 15.74   | 2.32               |
| %Male    | 38.91   | 54.34 | 66.80   | 4.78               |

(Fig. 2b). The proportion of the population age 65 and above ranged from 2.16 to 15.74%, with a mean of 7.37%. Villages with a high proportion of the population age 65 and above are mostly in the north to the eastern portion of Marinduque (Fig. 2c). The proportion of male population per village in Marinduque ranges from 38.91 to 66.80%, with a mean of 54.34%. Higher proportions of the male population were mostly in the inner and southern portion of the province (Fig. 2d). Table 2 summarizes the descriptive statistics of demographic indicators for COVID susceptibility of Marinduque.
mean of 46.11% per village. High-level poverty is apparent across Marinduque except on the northeastern side (Fig. 3d). Table 3 summarizes the descriptive statistics of socio-economic indicators for COVID susceptibility of Marinduque.

### 3.3 Geographic indicators

There are three (3) hospitals (Fig. 4a) in the province of Marinduque, (1) Dr. Damian Reyes Provincial Hospital; (2) Sta. Cruz District Hospital; and, (3) Torrijos Municipal Hospital (Table 4). The average distance of a village to the nearest hospital is around 12.57 km, the closest is within 0.35 km, while 33.00 km is the farthest. On average, a village is within 4.87 km far from the town centers with ranges from 0.15 to 16.89 km. Figure 4b shows the map of the distance of each village from town centers. There are three (3) main ports in Marinduque, namely: (1) Balanacan, (2) Cawit, and (3) Buyabod (Fig. 4c). The average distance of a village from a port is around 9.12 km, the nearest is within 1.02 km, while the farthest is 27.58 km. Meanwhile, the circumferential road in the province is considered its main highway connecting its six municipalities and the main route to town centers, ports, and hospitals (Fig. 4c). The average distance of a village is around 2.29 km from the provincial circumferential, the closest at 0.06 km, and the farthest is 13.66 km. Table 5 summarizes the descriptive statistics of geographic indicators for COVID susceptibility of Marinduque.
3.4 Susceptibility Index

Out of 12 principal components, only four (4) were included for calculation of the COVID-19 susceptibility scores (Fig. 5). These four (4) principal components explained around 64% of the variance (Table 6). Villages in the northwest and northeastern portion of the province are more susceptible to COVID-19 (Fig. 6). Also, areas within and near town centers score high compared to other villages in their respective municipalities. Villages within the town centers in Marinduque are mostly small in terms of the land area resulting in higher population density. Conversely, these town center main areas for commerce, religion, and socio-economic activities and government services, thus
higher population mobilities within and between these areas. Several studies have shown how population density \cite{44-47} and high population mobility \cite{48-51} have positively influenced COVID-19 transmission and number of cases. Coşkun et al. \cite{47} reported that population density and wind were the major factors that explained 94\% of the variability in the spread of COVID-19 in Turkies cities. Arif and Sengupta \cite{44} reported positive correlation between population density and COVID-19 cases in the four (4) states of Southern India. Copiello and Grillenzoni \cite{46} also reported strong relationship between population density and COVID-19 infection rate in China. Similar positive but moderate correlation between COVID cases was also reported by Bhadra et al. \cite{45} across India. Meanwhile, Manzira et al. \cite{52} reported that population mobility can explain 36.2\% of infection in Dublin City. According to Mu et al. \cite{53} higher population size and population density are among the factors that contribute to higher possibilities of contacts between people resulting in more risk of disease spread.

4 Conclusions

This study explores the use of GIS and PCA to develop a village-level COVID-19 susceptibility index for the province of Marinduque, Philippines. Results showed that the northwestern and northeastern portions of the Marinduque are more susceptible to COVID-19. Also, villages in the town centers of each municipality in the province have the same level of susceptibility. Meanwhile, there is some limitation in this study. Since the collection of CBMS data of Marinduque was in the year 2014, it may not represent the current situation, especially the proportion of children and the elderly population. Also, the calculation of geographic variables using Euclidean distance might differ from the actual distance. However, the results from this study can help the local government and concern agencies to develop plans and protocols to control the further spread of COVID in the province. For example, stricter social distancing protocols in the villages that are highly susceptible to COVID-19. Implementation of limited population mobility within and between areas with reported COVID cases. A COVID-19 outbreak in the province can be disastrous because of the limited capacity of its health care facilities. Therefore, all possible measures to control a potential outbreak must be explored. On the other hand, availability of COVID cases in at the village level in the province should be made readily accessible for different researchers to validate and further refine similar susceptibility model in this study. Furthermore, the use of real-time mobility data should also be explored to produce a timelier and near real time COVID susceptibility status of different villages in the province.

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Declarations

Competing interest The author declares no competing interest.

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based on integrating Common Weight Data Envelopment Analysis and principal component analysis models:

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