



Delineating village-level drought risk in Marinduque Island, Philippines

Arnold R. Salvacion¹

Received: 12 September 2022 / Accepted: 14 December 2022 / Published online: 26 December 2022
© The Author(s), under exclusive licence to Springer Nature B.V. 2022

Abstract

Islands are highly vulnerable to natural disasters and extreme weather events due to their physical size, remoteness, and limited resources. This paper measured village-level drought risk in Marinduque, Philippines using Principal Component Analysis (PCA) and fuzzy logic. Standard Precipitation Index was used to measure drought hazards in the province utilizing publicly available rainfall. Principal component analysis was used to derive the drought hazard index from SPI-calculated drought magnitude and total drought event at different time scales. The fuzzy logic approach was used to delineate the physical vulnerability of the province to drought. The social vulnerability index was also derived from the socioeconomic and demographic data of Marinduque using PCA. Based on the results, villages with high drought risk were found in the northwest and eastern portion of the province. The results showed that topography and climate influence the hazard and physical vulnerability to drought in the area. Villages in high mountainous regions, and areas with low rainfall have higher drought hazard and physical vulnerability scores. Meanwhile, villages with high social vulnerability are also those with a large population of women, the elderly, and households engage in agriculture.

Keywords Drought vulnerability · SPI · PCA · Fuzzy logic

1 Introduction

Small islands are small land masses surrounded by sea or ocean that are frequently prone to geological or hydrological disasters and most likely vulnerable to climate vulnerability and change (Ebi et al. 2006; Minamura et al. 2007; Polido et al. 2014; Salvacion and Magcale-Macandog 2015). According to Ebi et al. (2006) there are several features that constrain small islands to adapt to climate variability and change that includes: (a) small physical size; (b) remoteness; (c) limited natural resources; (d) sensitive economies to external shocks; (e) poorly developed infrastructure; (f) limited human and financial resources; (g) high population densities and growth rates; and

✉ Arnold R. Salvacion
arsalvacion@up.edu.ph

¹ Department of Community and Environmental Resource Planning College of Human Ecology, University of the Philippines Los Baños College, 4031 Laguna, Philippines

(h) vulnerability to disasters and extreme weather events. Such disasters and extreme weather events includes soil erosion, landslide, flooding, and drought.

Among natural hazards, drought is the most damaging and has long-lasting impact on both natural and human systems (Cook et al. 2007; Mishra and Singh 2010; OBrien et al. 2014; Edwards et al. 2015; Touma et al. 2015; Gerber and Mirzabaev 2017; Schwalm et al. 2017; Meza et al. 2020; Wu et al. 2020). Reported drought events around the world have resulted in water shortages, agricultural losses, reduction of hydro power supply, fires, famine, poor mental health, decrease in labor or productivity, and migration (OBrien et al. 2014; Edwards et al. 2015; Touma et al. 2015; Schwalm et al. 2017; Meza et al. 2020; Wu et al. 2020). Furthermore, drought events caused 20% of the global damage from disasters (Wilhite 2000; Gerber and Mirzabaev 2017). Drought occurs when there is a shortage in water availability due to inadequate rainfall or exceptionally high temperatures and low humidity, resulting in drying and loss of stored water resources (Haddow et al. 2017; Bullock et al. 2018). Drought can last from weeks to years varies in terms of spatial coverage, magnitude, and intensity (Hollins and Dodson 2013; Mishra et al. 2015). Droughts are classified into four general categories based on disciplinary viewpoints, namely: (1) meteorological; (2) hydrological; (3) agricultural; and (4) socio-economic (Mishra and Singh 2010; Hollins and Dodson 2013; Senay et al. 2015).

According to Sharafi et al. (2020), risk assessment is a type of risk knowledge creation that involved three (3) steps. The first step is the assessment of the danger or the identification of the nature, location, intensity, and probability of a threat. The second is the determination of the exposure and degree of vulnerability. The last step is the identification of available resources or coping capacities to address or manage threat or hazard. The result from risk assessment can help the decision makers and community to understand their exposure to various threats or hazards, and their physical, environmental, and socio-economic vulnerabilities (Zhang 2004; Sharafi et al. 2020). In the case of drought, the risk assessment involved hazard, exposure, and vulnerability analysis (Hayes et al. 2004). Drought hazard analysis is the quantification of drought frequency, magnitude, severity, and temporal trends (Hayes et al. 2004). Meanwhile, vulnerability assessment involves impact assessment (i.e. socio-economic, and environmental), causal assessment, and temporal trends (Hayes et al. 2004).

Vulnerability index is a composite measure to quantify vulnerability from combining and aggregating sub-indices or multiple single indicators (Garschagen and Romero-Lankao 2015; Reckien 2018). In the case of social vulnerability, it is done by combining sub-national socio-economic and demographic data using either variable addition or reduction approach (Cutter et al. 2003; Yoon 2012; Mavhura et al. 2017; Reckien 2018). The social vulnerability index is commonly constructed using a variable reduction approach through principal component analysis (PCA) to reduce a large number of potentially influential variables (Yoon 2012; Reckien 2018). In the principal component analysis, highly correlated variables are merged or grouped into similar units to form new variables (Mavhura et al. 2017; Reckien 2018). Meanwhile, for physical vulnerability, the fuzzy approach is also widely used (Rezaei et al. 2013; Mullick et al. 2019; Baučić 2020; Saha et al. 2021; Rashetnia and Jahanbani 2021). In the fuzzy approach, each of the values of the variable that can affect the physical vulnerability of an area is assigned a fuzzy membership from 0 to 1 (Rezaei et al. 2013; Lee et al. 2015; Mullick et al. 2019; Saha et al. 2021). Then, the fuzzy surface of the variable that measure physical vulnerability are combined or aggregated into a single physical vulnerability map (Rezaei et al. 2013; Lee et al. 2015; Mullick et al. 2019; Heydari Alamdarloo et al. 2020; Saha et al. 2021).

Similar to other small islands, Marinduque (Fig. 1) also manifests some of the constraints mentioned by Ebi et al. (2006). For example, the island province is 200 km south of the Philippine capital city, Manila, and will take 3 h to travel via ferry from mainland Luzon (Salvacion 2020; Lutero et al. 2022). Next, agriculture and fishing are the main livelihoods of the province which are highly sensitive to external shocks such as drought (Islam et al. 2014; Salvacion and Magcale-Macandog 2015; Tibesigwa et al. 2016). Previous studies have reported high population growth (Salvacion and Magcale-Macandog 2015), high poverty (Reyes and Due 2009; Salvacion 2018), high malnutrition (Salvacion 2017), and high erosion rates (Salvacion 2020). Recently, Prasetyo et al. (2020) studied the vulnerability of households in Marinduque to other natural hazards such as typhoons, landslides, and floods. The objective of this study is to assess the risk of drought at the village level in Marinduque Island, Philippines, by delineating the drought hazard, physical vulnerability, and social vulnerability of the province. In addition, it also aims to identify villages in Marinduque that are at high risk of drought to provide information for drought mitigation.



Fig. 1 Location map of Marinduque, Philippines

2 Methodology

2.1 Data

2.1.1 Climate data

In the absence of a weather station and a long record of rainfall data on the island of Marinduque, this study used a long series of rainfall data (1958–2019) from the TerraClimate database (Abatzoglou et al. 2018). According to Abatzoglou et al. (2018), TerraClimate is a high-spatial-resolution monthly climate data derived combining and interpolating high spatial resolution WorldClim database (Hijmans et al. 2005; Fick and Hijmans 2017) and a coarser resolution but time-varying monthly climatic data from Climate Research time series data version 4.0 (CRU Ts4.0) (Harris et al. 2014) and Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al. 2015). TerraClimate data include global monthly dataset of precipitation, maximum temperature, minimum temperature, wind speed, vapor pressure, solar radiation, and climatic water balance from 1958 to 2019 (Abatzoglou et al. 2018). Since the rainfall data from TerraClimate are approximately 4 km in spatial resolution, some villages are not covered. Therefore, TerraClimate data were further reduced to a spatial resolution of 1 km following the methodology of Salvacion et al. (2018) to generate rainfall data for all the villages in the province to generate rainfall data for all villages in the province (Table 1).

2.1.2 Physical data

Elevation data of Marinduque were downloaded and extracted from the advanced spaceborne thermal emission and reflection radiometer (ASTER) global digital elevation model (GDEM) (Abrams et al. 2015). The slope map of the province was generated from this elevation data (Salvacion 2016). The Marinduque land cover map was obtained from the Philippine Geoportal website (<https://www.geoportal.gov.ph/>). The soil data of the province was obtained from the Bureau of Soil and Water Management (BSWM) database. These variables affect the physical vulnerability of an area to drought (Jain et al. 2015; Dayal et al. 2018; Hoque et al. 2020, 2021; Heydari Alamdarloo et al. 2020).

2.1.3 Socioeconomic data

Socio-economic and demographic data (Table 2) used in this study were derived from the Community Based Monitoring System (CBMS) (Reyes et al. 2017) of the province for 2015. These socio-economic and demographic variables are assumed to influence drought vulnerability. For example, higher population density increases drought vulnerability (Shahid and Behrawan 2008; Jain et al. 2015). Similarly, higher population of children, female, and elderly increases vulnerability of an area to drought (Wang et al. 2020; Asmall et al. 2021; Salvador et al. 2021; Drysdale et al. 2021; Algur et al. 2021). A higher incidence of poverty and an unemployment rate also increases vulnerability to drought (Gebre et al. 2021; Drysdale et al. 2021). Lastly, dependence on agriculture, informal settlement, and lack of access to safe water magnify the impact of drought in an area (Shahid and Behrawan 2008; Calow et al. 2010; Twinomuhangi et al. 2021).

Table 1 Different socio-economic and demographic data from the community-based monitoring system (CBMS) used for the development of village-level social vulnerability index for drought in Marinduque, Philippines

Variables	Definition	Influence on drought vulnerability*	References
Population	Total number of individual	+	Shahid and Behrawan (2008), Jain et al. (2015)
Children population	Proportion of individuals from 0 to 5 years old	+	Asmall et al. (2021), Wang et al. (2020), Drysdale et al. (2021), Algur et al. (2021)
Female population	Proportion of individuals who are female	+	Shahid and Behrawan (2008), Algur et al. (2021)
Senior citizens	Proportion of individuals aged from 65 above	+	Salvador et al. (2021)
Income poor	Proportion of house with income below poverty threshold	+	Gebre et al. (2021)
Informal settlement	Proportion of individual considered as informal settlers	+	Twinomuhangi et al. (2021)
Agri engagement	Proportion of households in engaged in agriculture	+	Shahid and Behrawan (2008)
Unemployment rate	Unemployment rate of individuals 15 years old and above	+	Drysdale et al. (2021)
Access to safe water	Proportion of household without access to safe water	+	Calow et al. (2010)

* +sign means increase in the value of the variable increases drought vulnerability

Table 2 Classification of SPI values

Index value	Classification
2.0 and above	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
0.99 to –0.99	Near normal
–1.0 to –1.49	Moderately dry
–1.5 to –1.99	Severely dry
–2.0 and below	Extremely dry

2.2 Standardized precipitation index

The Standardized Precipitation Index (SPI) (McKee et al. 1993) is a common tool for assessing and quantifying drought in an area (Mishra and Singh 2010; Santos et al. 2011; Tirivarombo et al. 2018; Singh et al. 2019). The SPI uses long-term records (30 years or greater) of monthly rainfall data to identify drought event, quantify its magnitude, and eventually map its spatial extent multiple time scale (McKee et al. 1993; Mishra and Singh 2010; Awchi and Kalyana 2017; Tirivarombo et al. 2018; Singh et al. 2019). By using SPI, a long series of monthly rainfall data was fitted using the gamma probability distribution function (Eq. 1) and converted to normal distribution to further calculate the number of standard deviation (Eq. 2) that the observed precipitation deviates from the long-term mean (McKee et al. 1993; Tirivarombo et al. 2018; Singh et al. 2019). The calculated SPI values are then classified into different categories (Table 2) to determine if a particular month is considered to be a moderate, severe, or extreme dry event (McKee et al. 1993; Mishra and Singh 2010; Tirivarombo et al. 2018; Singh et al. 2019). According to the World Meteorological Organization (2012), SPI can be used to assess different kinds of drought based on different SPI scale. For example, 1- or 2- month SPI can be used to assess meteorological drought, 1–6-month SPI for agricultural drought, and 6- up to 24-month or more for hydrological drought.

$$G(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \text{ for } x > 0 \quad (1)$$

where $\alpha > 0$ is the shape parameter, $\beta > 0$ is the scale parameter, $x > 0$ is the amount of precipitation, and $\Gamma(\alpha)$ is the gamma function

$$\text{SPI} = \frac{x_i - \bar{x}}{\sigma} \quad (2)$$

where x_i is the precipitation during the month i , \bar{x} and σ is the mean and standard deviation of the long-term precipitation record.

2.3 Drought hazard assessment

Drought magnitude and duration in the province for different SPI scale was derived from downscaled TerraClimate data from 1958 to 2019 for Marinduque. Drought magnitude was calculated using Eq. (3) (Suryabagavan 2017; Singh et al. 2019). Drought duration is the total number of consecutive months (at least 2 months) where $\text{SPI} \leq -1$ (Spinoni et al. 2014,

2019). In this study, the total number of drought events ($SPI \leq -1$ of at least 2 months) was calculated instead. Village-level drought characteristics were extracted using the modal value for each village boundary or polygon. To generate a single drought hazard index, drought magnitude, and the total number of drought events for each SPI scale (Table 3) were combined using PCA (Salvacion 2022a).

$$DM = -\left(\sum_{j=1}^x SPI_{ij}\right) \tag{3}$$

where j is the first month when SPI_i is less than or equal to the threshold (-1) and continues for x months until SPI_i is greater than the threshold (-1). i represents the scale (i.e. 1-, 3-, 6-, and 12- month) used for SPI calculation. $SPI \leq -1$ is classified as drought events (see Table 2).

2.4 Physical vulnerability assessment

Physical vulnerability assessment was done using a fuzzy logic approach using elevation, slope, soil, and land cover map of Marinduque as input data (Zadeh 1965; Dayal et al. 2018). Equation 4 was used to calculate fuzzy membership value for elevation and slope. Meanwhile, fuzzy membership value for land cover and soil texture was assigned based on their respective classes (Dayal et al. 2018; Hoque et al. 2020, 2021). The arithmetic mean was used to aggregate the fuzzy membership maps of the different variables (i.e., elevation, slope, soil, and land cover) and derived the final physical vulnerability map of the province. Zonal statistics (i.e., mean) of the physical vulnerability map for each village was calculated to generate village-level vulnerability measure.

$$FMV = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & x > b \end{cases} \tag{4}$$

where FMV is the fuzzy membership value, x is value of the input surface, a is minimum value threshold, b is the maximum value threshold.

Table 3 Different drought characteristics for each SPI scale used to develop drought hazard index for Marinduque, Philippines

Variable	Definition
SPI _{1S}	Drought severity based on 1-month SPI
SPI _{3S}	Drought severity based on 3-month SPI
SPI _{6S}	Drought severity based on 6-month SPI
SPI _{12S}	Drought severity based on 12-month SPI
SPI _{1D}	Total drought events based on 1-month SPI
SPI _{3D}	Total drought events based on 3-month SPI
SPI _{6D}	Total drought events based on 6-month SPI
SPI _{12D}	Total drought events based on 12-month SPI

2.5 Social vulnerability assessment

Principal component analysis was used to generate social vulnerability index to drought for each village in the province based on the socio-economic and demographic data from CBMS. Index scores for social vulnerability were calculated by summing the factor loading of the principal components with eigenvalue >1 (Abson et al. 2012; Rabby et al. 2019; Ravago et al. 2020). Social vulnerability index was normalized using min–max rescaling transformation (Eq. 5).

$$NV = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (5)$$

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 maximum value of the index.

2.6 Drought risk assessment

Again, zonal statistics were calculated for drought hazard and physical vulnerability maps to generate village-level data for these measures. This was done to match the aggregation level of the social vulnerability index. Then, drought risk index was derived by multiplying the hazard index with the physical and social vulnerability indices (Singh et al. 2019).

3 Results

3.1 Drought hazard

Figure 2 shows the spatial pattern of the magnitude of the accumulated drought using a different SPI scale from 1958 to 2019. For SPI₁, the higher magnitude was observed in the mid-eastern to the eastern portion of the province or mostly villages in the municipalities of Sta. Cruz and Torrijos (Fig. 2a). For SPI₃, higher magnitude was observed in the western portion of the province affecting some part of the municipalities of Boac and Gasan (Fig. 2b). The spatial pattern of magnitude for SPI₆ is almost uniform across the province but with higher values observed in the northern part of the province (Fig. 2c). Lastly, higher drought magnitude for SPI₁₂ was mostly concentrated on the northern part of the province affecting mostly villages in the municipality of Mogpog and some part of Sta. Cruz (Fig. 2d).

Figure 3 shows the spatial distribution of total dry events per village in Marinduque, the Philippines, from 1958 to 2019. According to SPI₁, there are more drought events in the northeast part of the province (Fig. 3a). Based in SPI₃, villages on the bottom half of the province, specifically the eastern part, experienced more drought events (Fig. 3b). Based on SPI₆, with more events affecting the north to the eastern part of the island (Fig. 3c). Lastly, for SPI₁₂, there more drought events in the northern part of the Marinduque (Fig. 3d). Based on the eigenvalue, three (3) principal components can be used to develop a drought hazard index for Marinduque. These three (3) principal components can explain 83% of the total variance of drought magnitude and the total number of drought events for each SPI

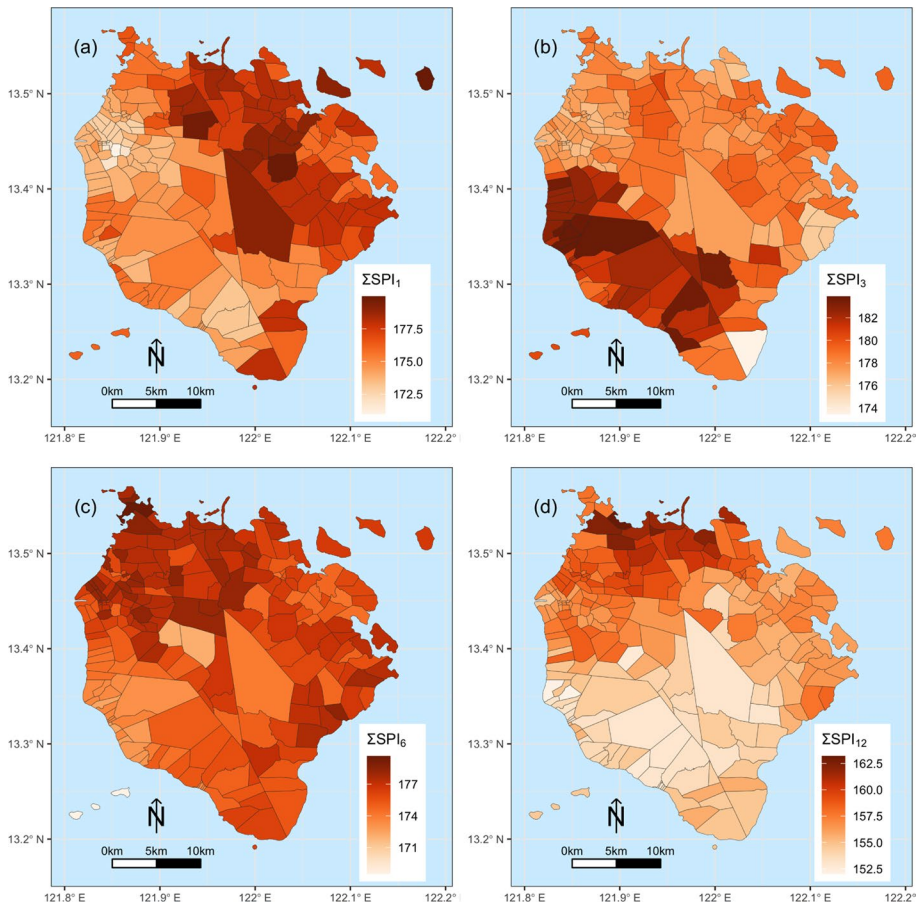


Fig. 2 Accumulated drought magnitude map of Marinduque based on **a** SPI₁, **b** SPI₃, **c** SPI₆, and **d** SPI₁₂ from 1958 to 2019

scale (Table 4). Figure 4 shows the map of the Marinduque village-level drought hazard index, Philippines. A higher drought risk was observed in the north, east, and southern portions of the province.

3.2 Physical characteristics and physical vulnerability

Figure 5 shows the different physical map of Marinduque (i.e., elevation, slope, soil texture, and land cover). The elevation (Fig. 5a) of the province shows that the inner portion of the province is composed of mountainous areas with mostly rolling terrain (Fig. 5b). Also, large part of the province has clay loam and small pockets of sandy soil in some coastal and riverine areas (Fig. 5c). In terms of land cover, agricultural land (perennial and annual crops) dominates the province (Fig. 5d). Meanwhile, physical vulnerability index map (Fig. 6) shows that villages in the inner portion of Marinduque have high physical vulnerability to drought compared to villages in the flat and low-lying region of the province.

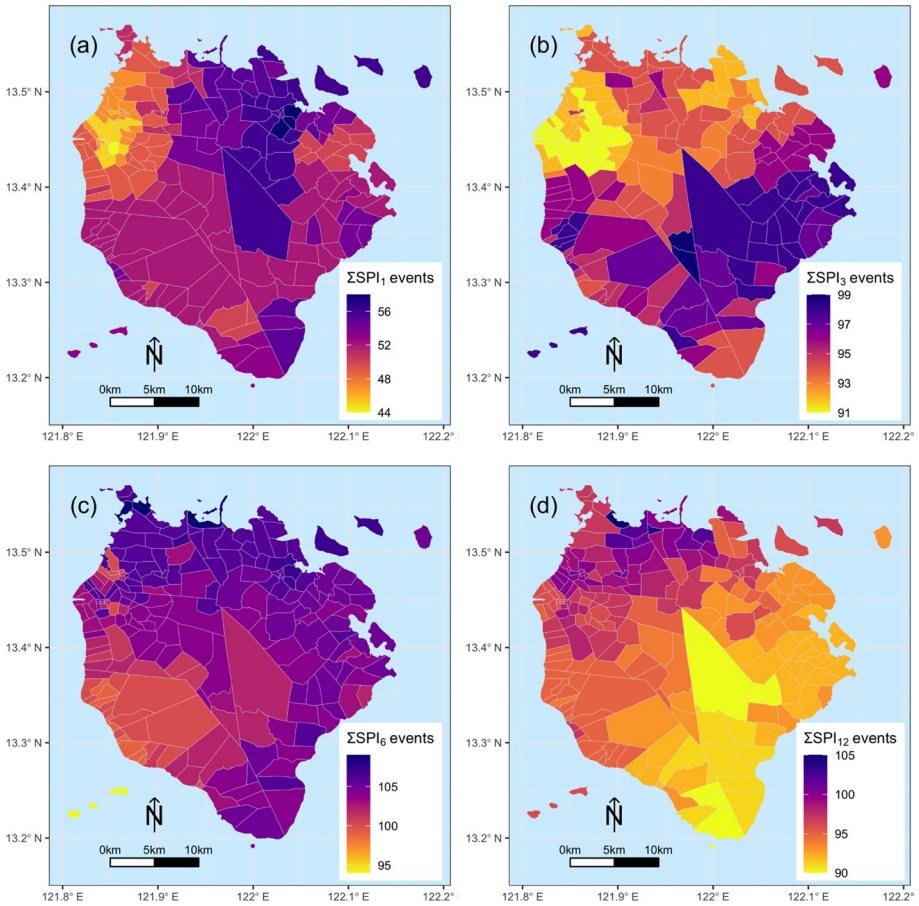


Fig. 3 Total number of drought event map of Marinduque based on **a** SPI₁, **b** SPI₃, **c** SPI₆, and **d** SPI₁₂ from 1958 to 2019

Table 4 Principal components eigen values of hazard index

Principal components	Eigenvalue	Variance explained (%)	Cumulative variance explained (%)
PC1	1.88	0.44	0.44
PC2	1.43	0.26	0.70
PC3	1.01	0.13	0.83
PC4	0.76	0.07	0.90
PC5	0.62	0.05	0.95
PC6	0.44	0.02	0.97
PC7	0.36	0.02	0.99
PC8	0.32	0.01	1.00

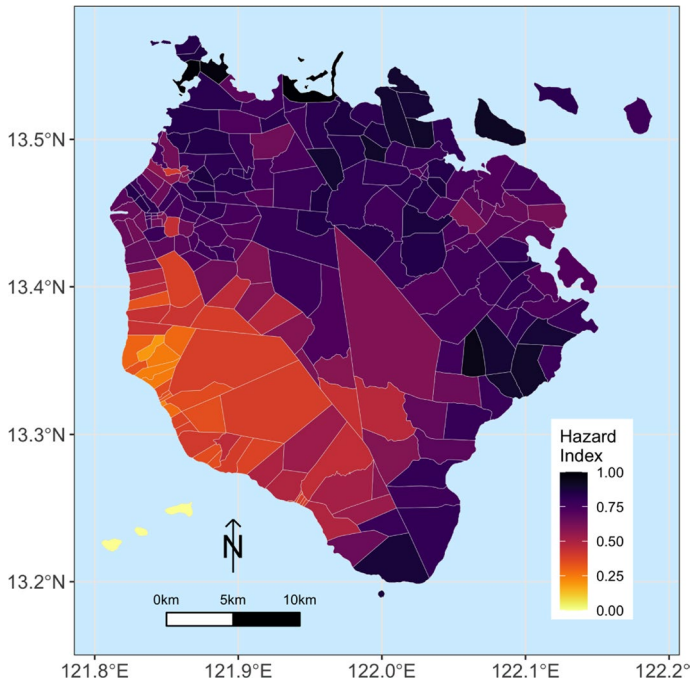


Fig. 4 Drought hazard map of Marinduque, Philippines

3.3 Socio-demographic characteristics and social vulnerability

Data from the CBMS showed that there is a high proportion of unemployment (Fig. 7a), engagement of agriculture (Fig. 7b), and poverty in the province (Fig. 7c). There were also villages with a higher proportion of informal settlers (Fig. 7d) and do not have access to safe water (Fig. 7e). Meanwhile, there is also a high proportion of the female population in some villages (Fig. 7f). Conversely, the proportion of children (Fig. 7g), aged (senior citizen) (Fig. 7h) population and total population (Fig. 7i) also varies across villages in Marinduque. Table 5 shows the descriptive statistics of different socioeconomic and demographic data from Marinduque CBMS. Based on the eigenvalue four (4) principal components can be used to develop a social vulnerability index to drought for Marinduque. These four (4) principal components can explain 69% of the total variance of socioeconomic and demographic indicators of drought vulnerability (Table 6). Figure 8 shows the village-level social vulnerability index of Marinduque, Philippines. It shows that social vulnerability to drought in Marinduque varies spatially with high-risk areas distributed throughout the province.

3.4 Drought risk

Figure 9 shows the drought risk map for Marinduque, Philippines. Higher drought risk was calculated for the northwestern to the eastern portion of the province. The highest risk of drought is observed in mountainous regions of the province, except for some areas in the

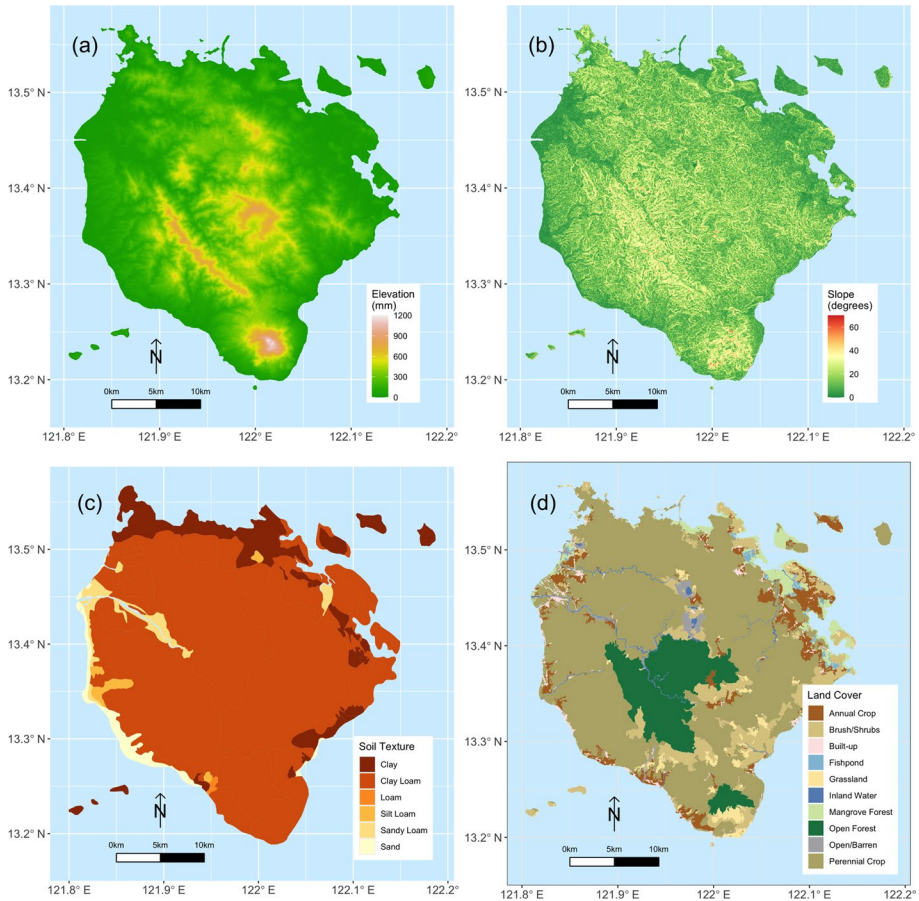


Fig. 5 Elevation **a**, slope **b**; soil texture **c**; and land cover **d** map of Marinduque, Philippines

coastal and town center of the province capital municipality of Boac. The ranking of villages in terms of risk score shows that 8 out of the top 10 villages with the highest risk score are located in the municipality of Sta. Cruz (Table 7).

4 Discussion

The spatial pattern of drought magnitude and duration based on the SPI scale vary in the province. It means that the occurrence and duration of short- to long-term drought events differ across the province of Marinduque. However, combining variables on drought magnitude and duration reveal that pockets of low drought hazard areas in the southwestern portion of the province. According to Xie et al. (2018) regionalization of drought occurrence is largely associated with topography and climate. In the case of Marinduque, villages in the western part of the province usually have low elevation and high rainfall (Salvacion 2022b). The effect of topography is also evident in the physical vulnerability to drought of villages in the province. Higher physical vulnerability was observed in villages

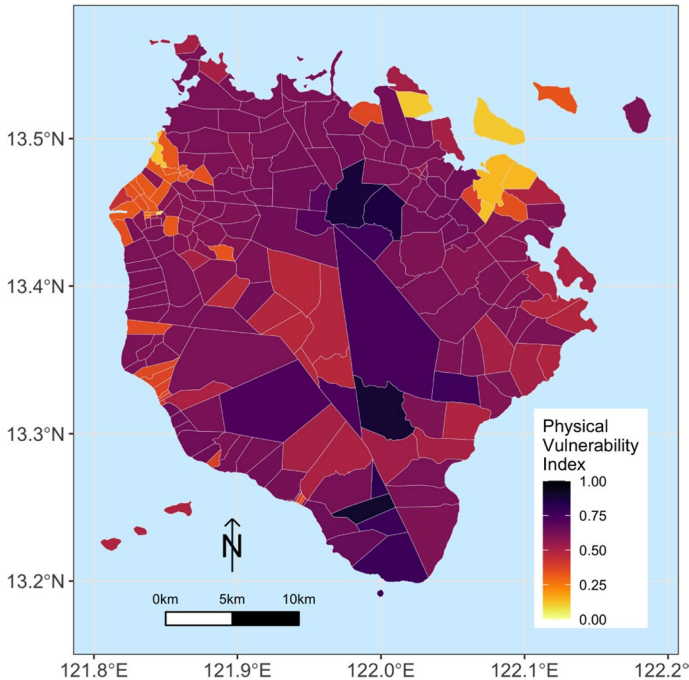


Fig. 6 Physical vulnerability to drought map of Marinduque

in the mountainous part of the province characterized by high elevation and sloping terrain. High elevation and steeper slope translate into low ground water infiltration and recharge rate (Thapa et al. 2017; Miraki et al. 2019). On the other hand, high social vulnerability scores were observed in villages with a high proportion of households engaged in agriculture, proportions of aged (senior citizen), and female populations. Agriculture is highly sensitive to drought because limited water availability significantly affects crop productivity (Leng and Hall 2019) and livestock production (Murray-Tortarolo and Jaramillo 2019). Meanwhile, women and the elderly are considered a vulnerable population to environmental hazards. According to Rukmana (2014), informal employment, lower wages, and family care responsibility hinder recovery time for women after a disaster, while elderly people depend on others for care due to poor physical health.

The provincial government of Marinduque should explore potential measures on how to address the high drought hazard and vulnerability situation of the identified villages. There are three (3) categories of drought mitigation measures, namely: (1) water-supply measures; (2) water demand measures; and (3) impact minimization measures (Rossi 2000; Yang and Liu 2020). The first two measures address the issue of water scarcity, while the third measure aims to reduce the social, economic, and environmental impact of drought (Yang and Liu 2020). Improvement of the existing water system and construction of new reservoirs to increase water storage capacity are some of the structural measures to address the potential water scarcity due to drought. They can also explore rainfall harvesting through the development of small water impoundments (Contreras et al. 2013). It consists of rainfall harvesting and storage structures such as canal facilities, spillways, outlet works, and earth embankment (Contreras et al. 2013). These structures can store and collect water direct from rainfall and surface run-off for future use as

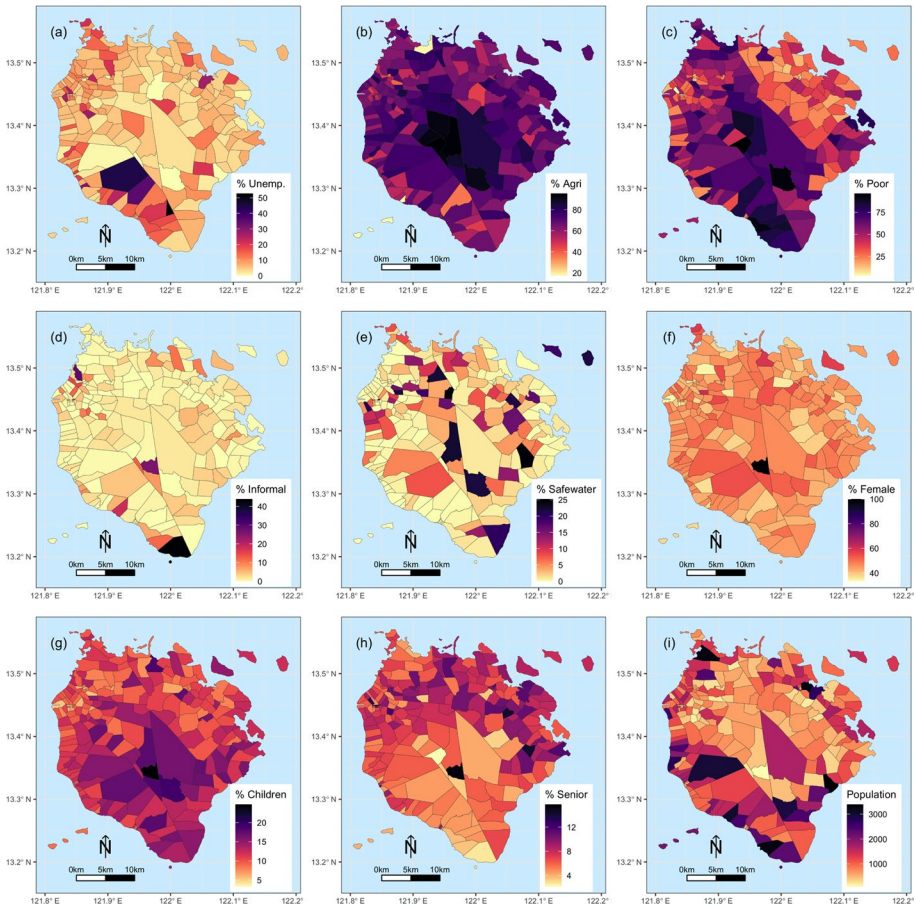


Fig. 7 Map of different socioeconomic and demographic variables used to for development of drought vulnerability index for Marinduque, Philippines: **a** total population; **b** children population; **c** female population; **d** senior citizen population; **e** population engage in agriculture; **f** proportion of household without access to safe water; **g** informal settlers; **h** unemployment; and, **i** poverty incidence

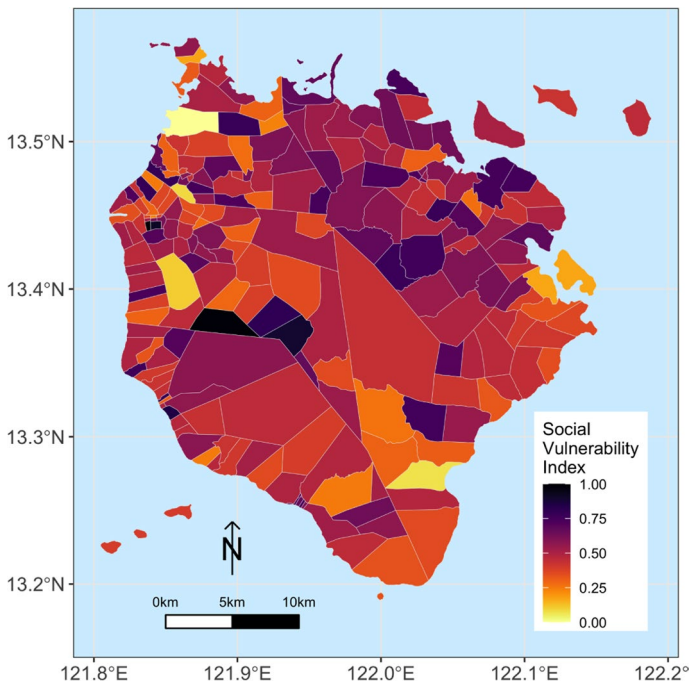
well as address unbalance rainfall distribution in the Philippines (Contreras et al. 2013). The provincial government can also examine the socio-economic and demographic factors contribute to the high vulnerability of villages to address the socio-economic impact of drought can and reflect on their ability (e.g. fiscal capability, and service implementation) to respond to drought hazard. According to Cutter et al. (2003) social vulnerability deals with the social factors and community characteristics and the ability of their government to natural hazards. Measures the lack of individual, group, or community ability to adapt and cope with any external stressor on their livelihood and well-being (Füssel 2012; Otto et al. 2017). For example, targeted interventions to those villages with high proportions of the household involved in the agricultural sector, high poverty incidence, and high unemployment rate can be implemented. Consequently, the provincial government should also develop plans to address not only drought but other meteorological hazards (i.e. flooding) to increase resilience in the province. According to MacDonald et al. (2020), exposure of island communities to consecutive atmospheric

Table 5 Descriptive statistics of socio-economic and demographic data of Marinduque, Philippines

Variable	Definition	Minimum	Mean	Maximum	Standard deviation
Population	Total number of individual	170	1080	3389	680
Children population	Proportion of individuals from 0 to 5 years old	3.31	11.41	24.70	3.02
Female population	Proportion of individuals who are female	33.20	45.66	61.09	4.77
Senior citizens	Proportion of individuals aged from 65 above	2.16	7.37	15.74	2.32
Income poor	Proportion of house with income below poverty threshold	3.30	46.11	96.20	20.25
Informal settlement	Proportion of individual considered as informal settlers	0	2.60	43.85	4.89
Agri engagement	Proportion of households in engaged in agriculture	17.32	65.88	95.38	12.27
Unemployment rate	Unemployment rate of individuals 15 years old and above	0	8.42	52.76	7.18
Access to safe water	Proportion of household without access to safe water	0	3.76	25.20	5.85

Table 6 Principal components eigen values of vulnerability index

Principal components	Eigenvalue	Variance explained (%)	Cumulative variance explained (%)
PC1	1.54	0.26	0.26
PC2	1.32	0.19	0.46
PC3	1.04	0.12	0.58
PC4	1.02	0.12	0.69
PC5	0.89	0.09	0.78
PC6	0.86	0.08	0.86
PC7	0.78	0.07	0.93
PC8	0.58	0.04	0.97
PC9	0.53	0.03	1.00

**Fig. 8** Social vulnerability to drought map of Marinduque, Philippines

hazards such as drought and flood can lower resilience and reduce its scarce water resources.

Meanwhile, the methodology and data used in this study have their limitations. There is inherent uncertainty in gridded climatic data due to the interpolation and extrapolation methodology, climate homogeneities, and changes in the availability of data through time (Dunn et al. 2014; Prein and Gobiet 2017; Abatzoglou et al. 2018; Parkes et al. 2019). Also, in the case of Marinduque, there are no long series of climatic records that can be used to evaluate the accuracy of TerraClimate. However, several researchers around the

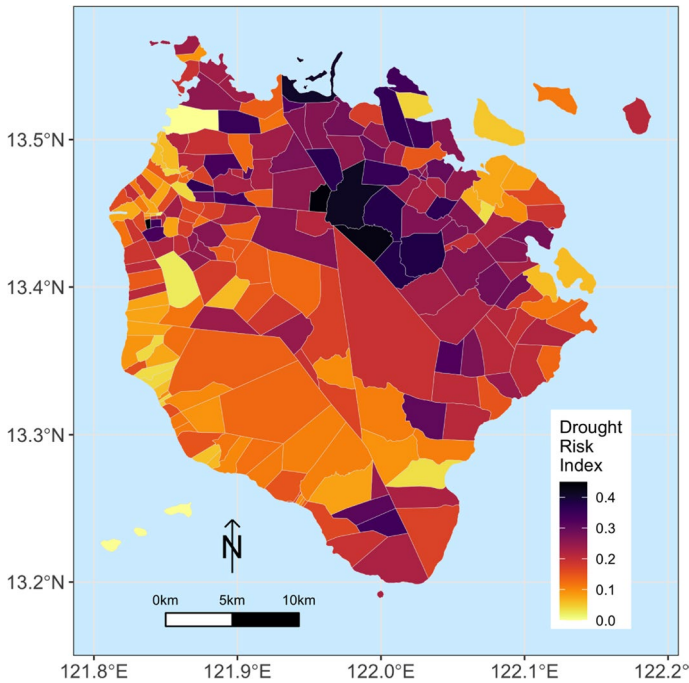


Fig. 9 Drought risk map of Marinduque, Philippines

Table 7 Top 10 high drought risk villages in Marinduque

Rank	Village	Municipality	Drought hazard	Physical vulnerability	Social vulnerability	Drought risk score
1	Isok II Poblacion	Boac	0.76	0.59	1.00	0.45
2	Puting Buhangin	Mogpog	0.85	0.70	0.74	0.44
3	Labo	Santa Cruz	0.84	0.76	0.67	0.43
4	San Antonio	Santa Cruz	0.81	0.87	0.59	0.41
5	Botilao	Santa Cruz	1.00	0.61	0.67	0.41
6	Devilla	Santa Cruz	0.84	0.60	0.75	0.38
7	Makulapnit	Santa Cruz	0.79	0.62	0.77	0.38
8	Kilo–Kilo	Santa Cruz	0.76	0.86	0.57	0.38
9	Lamesa	Santa Cruz	0.89	0.62	0.67	0.37
10	Baguidbirin	Santa Cruz	0.74	0.63	0.77	0.36

world have adopted TerraClimate in their studies (e.g. Baquero and Machado 2018; Xu et al. 2019; Zhao et al. 2019; Wang et al. 2020; Wu et al. 2020; Kath et al. 2020). On the other hand, the use of SPI has several disadvantages and advantages (Hayes et al. 1999). The output of SPI is highly dependent on the quality of input data (Hayes et al. 1999). Furthermore, since SPI uses only rainfall data, it cannot be used to account for the effects of increasing temperature under future climate change conditions (Vicente-Serrano et al. 2010). On the contrary, since SPI only requires rainfall as input, this makes the index

simple and flexible in identifying droughts at different time scales (Hayes et al. 1999). SPI also provides a consistent severe and extreme drought classification for any time scales and locations (Hayes et al. 1999). In the case of the Philippines, the SPI derived from TerraClimate data agrees with previously reported drought events in different locations in the country (Salvacion 2021).

5 Conclusion

This study measured the risk of drought at the village level in the island province of Marinduque, Philippines. It combined the use of PCA and the fuzzy logic approach to calculate the hazard of drought at the village level, the social vulnerability, and the physical vulnerability score in the province. The results showed that topography and climate influence the hazard and physical vulnerability to drought in the province. Villages located in high mountainous regions with low rainfall have higher drought hazard and physical vulnerability scores. Meanwhile, villages with high social vulnerability are also those with a large population of women, elderly, and household to engage in agriculture. Results from this study can be used to develop plans and policies to mitigate and reduce the potential impact of future drought events in the province. The approach used in this study can be replicated in other areas of the country. However, further studies and future validation of such an approach, especially in similar areas with limited data availability, are highly recommended.

Acknowledgements The author would like to acknowledge the help of the Marinduque Provincial Government and the Provincial Planning Development Office for providing the latest CBMS data of the province, especially Ms. Rocy Moreno and Mr. Richard Calub.

Funding The author received no financial support for the research, authorship, and/or publication of this article.

Declarations

Conflict of interest The author declare no competing interest.

References

- Abatzoglou JT, Dobrowski SZ, Parks SA, Hegewisch KC (2018) TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Sci Data* 5:1–12. <https://doi.org/10.1038/sdata.2017.191>
- Abrams M, Tsu H, Hulley G et al (2015) The Advanced Spaceborne thermal emission and reflection radiometer (ASTER) after fifteen years: review of global products. *Int J Appl Earth Obs Geoinf* 38:292–301. <https://doi.org/10.1016/j.jag.2015.01.013>
- Abson DJ, Dougill AJ, Stringer LC (2012) Using principal component analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. *Appl Geogr* 35:515–524. <https://doi.org/10.1016/j.apgeog.2012.08.004>
- Algur KD, Patel SK, Chauhan S (2021) The impact of drought on the health and livelihoods of women and children in India: a systematic review. *Child Youth Serv Rev* 122:105909. <https://doi.org/10.1016/j.childyouth.2020.105909>
- Asmall T, Abrams A, Rössli M et al (2021) The adverse health effects associated with drought in Africa. *Sci Total Environ*. <https://doi.org/10.1016/j.scitotenv.2021.148500>
- Awchi TA, Kalyana MM (2017) Meteorological drought analysis in northern Iraq using SPI and GIS. *Sustain Water Resour Manag* 3:451–463. <https://doi.org/10.1007/s40899-017-0111-x>

- Baquero OS, Machado G (2018) Spatiotemporal dynamics and risk factors for human Leptospirosis in Brazil. *Sci Rep*. <https://doi.org/10.1038/s41598-018-33381-3>
- Baučić M (2020) Household level vulnerability analysis—index and fuzzy based methods. *ISPRS Int J Geo Inf* 9:263. <https://doi.org/10.3390/ijgi9040263>
- Bullock JA, Haddow GD, Coppola DP (2018) 3 - Hazards. In: Bullock JA, Haddow GD, Coppola DP (eds) *Homeland security* (second edition). Butterworth-Heinemann, pp 45–66
- Calow RC, MacDonald AM, Nicol AL, Robins NS (2010) Ground water security and drought in Africa: linking availability, access, and demand. *Ground Water* 48:246–256. <https://doi.org/10.1111/j.1745-6584.2009.00558.x>
- Contreras SM, Sandoval TS, Tejada SQ (2013) Rainwater harvesting, its prospects and challenges in the uplands of Talugtog, Nueva Ecija, Philippines. *Int Soil Water Conserv Res* 1:56–67. [https://doi.org/10.1016/S2095-6339\(15\)30031-9](https://doi.org/10.1016/S2095-6339(15)30031-9)
- Cook ER, Seager R, Cane MA, Stahle DW (2007) North American drought: reconstructions, causes, and consequences. *Earth Sci Rev* 81:93–134. <https://doi.org/10.1016/j.earscirev.2006.12.002>
- Cutter SL, Boruff BJ, Shirley WL (2003) Social vulnerability to environmental hazards. *Soc Sci Q* 84:242–261. <https://doi.org/10.1111/1540-6237.8402002>
- Dayal KS, Deo RC, Apan AA (2018) Spatio-temporal drought risk mapping approach and its application in the drought-prone region of south-east Queensland, Australia. *Nat Hazards* 93:823–847. <https://doi.org/10.1007/s11069-018-3326-8>
- Drysdale RE, Bob U, Moshabela M (2021) Socio-economic determinants of increasing household food insecurity during and after a drought in the district of iLembe, South Africa. *Ecol Food Nutr* 60:25–43. <https://doi.org/10.1080/03670244.2020.1783663>
- Dunn RJH, Donat MG, Alexander LV (2014) Investigating uncertainties in global gridded datasets of climate extremes. *Clim past* 10:2171–2199. <https://doi.org/10.5194/cp-10-2171-2014>
- Ebi KL, Lewis ND, Corvalan C (2006) Climate variability and change and their potential health effects in small island states: information for adaptation planning in the health sector. *Environ Health Perspect* 114:1957–1963. <https://doi.org/10.1289/ehp.8429>
- Edwards B, Gray M, Hunter B (2015) The impact of drought on mental health in rural and regional Australia. *Soc Indic Res* 121:177–194. <https://doi.org/10.1007/s11205-014-0638-2>
- Fick SE, Hijmans RJ (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *Int J Climatol* 37:4302–4315. <https://doi.org/10.1002/joc.5086>
- Füssel H-M (2012) Vulnerability to Climate Change and Poverty. In: Edenhofer O, Wallacher J, Lotze-Campen H et al (eds) *Climate change, justice and sustainability: linking climate and development policy*. Springer, Netherlands, pp 9–17
- Garschagen M, Romero-Lankao P (2015) Exploring the relationships between urbanization trends and climate change vulnerability. *Clim Change* 133:37–52. <https://doi.org/10.1007/s10584-013-0812-6>
- Gebre B, Ayenew HY, Biadgilign S (2021) Drought, hunger and coping mechanisms among rural household in Southeast Ethiopia. *Heliyon*. <https://doi.org/10.1016/j.heliyon.2021.e06355>
- Gerber N, Mirzabaev A (2017) Benefits of action and costs of inaction: drought mitigation and preparedness: a literature review
- Haddow GD, Bullock JA, Coppola DP (2017) 2 - Natural and Technological Hazards and Risk Assessment. In: Haddow GD, Bullock JA, Coppola DP (eds) *Introduction to emergency management* (Sixth Edition). Butterworth-Heinemann, pp 33–77
- Harris I, Jones PD, Osborn TJ, Lister DH (2014) Updated high-resolution grids of monthly climatic observations: the CRU TS3.10 dataset. *Int J Climatol* 34:623–642. <https://doi.org/10.1002/joc.3711>
- Hayes MJ, Svoboda MD, Wihite DA, Vanyarkho OV (1999) Monitoring the 1996 drought using the standardized precipitation index. *Bull Am Meteor Soc* 80:429–438. [https://doi.org/10.1175/1520-0477\(1999\)080%3c0429:MTDUTS%3e2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080%3c0429:MTDUTS%3e2.0.CO;2)
- Hayes MJ, Wilhelmi OV, Knutson CL (2004) Reducing drought risk: bridging theory and practice. *Nat Hazard Rev* 5:106–113. [https://doi.org/10.1061/\(ASCE\)1527-6988\(2004\)5:2\(106\)](https://doi.org/10.1061/(ASCE)1527-6988(2004)5:2(106))
- Heydari Alamdarloo E, Khosravi H, Nasabpour S, Gholami A (2020) Assessment of drought hazard, vulnerability and risk in Iran using GIS techniques. *J Arid Land* 12:984–1000. <https://doi.org/10.1007/s40333-020-0096-4>
- Hijmans RJ, Cameron SE, Parra JL et al (2005) Very high resolution interpolated climate surfaces for global land areas. *Int J Climatol* 25:1965–1978. <https://doi.org/10.1002/joc.1276>
- Hollins S, Dodson J (2013) Drought. In: Peter T B (ed) *Encyclopedia of natural hazards*. Springer, Netherlands, pp 189–197
- Hoque M, Pradhan B, Ahmed N, Alamri A (2021) Drought vulnerability assessment using geospatial techniques in Southern Queensland Australia. *Sensors* 21:6896. <https://doi.org/10.3390/s21206896>

- Hoque MA-A, Pradhan B, Ahmed N (2020) Assessing drought vulnerability using geospatial techniques in northwestern part of Bangladesh. *Sci Total Environ* 705:135957. <https://doi.org/10.1016/j.scitotenv.2019.135957>
- Islam MdM, Sallu S, Hubacek K, Paavola J (2014) Vulnerability of fishery-based livelihoods to the impacts of climate variability and change: insights from coastal Bangladesh. *Reg Environ Change* 14:281–294. <https://doi.org/10.1007/s10113-013-0487-6>
- Jain VK, Pandey RP, Jain MK (2015) Spatio-temporal assessment of vulnerability to drought. *Nat Hazards* 76:443–469. <https://doi.org/10.1007/s11069-014-1502-z>
- Kath J, Byrareddy VM, Craparo A et al (2020) Not so robust: Robusta coffee production is highly sensitive to temperature. *Glob Change Biol* 26:3677–3688. <https://doi.org/10.1111/gcb.15097>
- Kobayashi S, Ota Y, Harada Y et al (2015) The JRA-55 reanalysis: general specifications and basic characteristics. *J Meteorol Soc Jpn* 93:5–48. <https://doi.org/10.2151/jmsj.2015-001>
- Lee M-J, Kang JE, Kim G (2015) Application of fuzzy combination operators to flood vulnerability assessments in Seoul, Korea. *Geocarto Int* 30:1052–1075. <https://doi.org/10.1080/10106049.2015.1027290>
- Leng G, Hall J (2019) Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Sci Total Environ* 654:811–821. <https://doi.org/10.1016/j.scitotenv.2018.10.434>
- Lutero DS, Cerilo GEA, Eustaquio AM et al (2022) Optimal route planning for day tours in Marinduque, Philippines. *Spat Inf Res* 30:205–214. <https://doi.org/10.1007/s41324-021-00424-3>
- MacDonald MC, Elliott M, Langidrik D et al (2020) Mitigating drought impacts in remote island atolls with traditional water usage behaviors and modern technology. *Sci Total Environ* 741:140230. <https://doi.org/10.1016/j.scitotenv.2020.140230>
- Mavhura E, Manyena B, Collins AE (2017) An approach for measuring social vulnerability in context: the case of flood hazards in Muzarabani district, Zimbabwe. *Geoforum* 86:103–117. <https://doi.org/10.1016/j.geoforum.2017.09.008>
- McKee TB, Doesken NJ, Kleist J (1993) Relationship of drought frequency and duration to time scales. Anaheim, California
- Meza I, Siebert S, Döll P et al (2020) Global-scale drought risk assessment for agricultural systems. *Nat Hazard* 20:695–712. <https://doi.org/10.5194/nhess-20-695-2020>
- Minamura N, Nurse L, McLean R et al (2007) Small islands. In: Parry ML, Canziani OF, Palutikof JP et al (eds) Contribution of working group ii to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, pp 687–716
- Miraki S, Zanganeh SH, Chapi K et al (2019) Mapping groundwater potential using a novel hybrid intelligence approach. *Water Resour Manage* 33:281–302. <https://doi.org/10.1007/s11269-018-2102-6>
- Mishra AK, Ines AVM, Das NN et al (2015) Anatomy of a local-scale drought: application of assimilated remote sensing products, crop model, and statistical methods to an agricultural drought study. *J Hydrol* 526:15–29. <https://doi.org/10.1016/j.jhydrol.2014.10.038>
- Mishra AK, Singh VP (2010) A review of drought concepts. *J Hydrol* 391:202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
- Mullick MdRA, Tanim AH, Islam SMS (2019) Coastal vulnerability analysis of Bangladesh coast using fuzzy logic based geospatial techniques. *Ocean Coast Manag* 174:154–169. <https://doi.org/10.1016/j.ocecoaman.2019.03.010>
- Murray-Tortarolo GN, Jaramillo VJ (2019) The impact of extreme weather events on livestock populations: the case of the 2011 drought in Mexico. *Clim Change* 153:79–89. <https://doi.org/10.1007/s10584-019-02373-1>
- O'Brien LV, Berry HL, Coleman C, Hanigan IC (2014) Drought as a mental health exposure. *Environ Res* 131:181–187. <https://doi.org/10.1016/j.envres.2014.03.014>
- Otto IM, Reckien D, Reyer CPO et al (2017) Social vulnerability to climate change: a review of concepts and evidence. *Reg Environ Change* 17:1651–1662. <https://doi.org/10.1007/s10113-017-1105-9>
- Parkes B, Higginbottom TP, Hufkens K et al (2019) Weather dataset choice introduces uncertainty to estimates of crop yield responses to climate variability and change. *Environ Res Lett* 14:124089. <https://doi.org/10.1088/1748-9326/ab5ebb>
- Polido A, João E, Ramos TB (2014) Sustainability approaches and strategic environmental assessment in small islands: an integrative review. *Ocean Coast Manag* 96:138–148. <https://doi.org/10.1016/j.ocecoaman.2014.05.005>
- Prasetyo YT, Senoro DB, German JD, Robielos RAC, Ney FP (2020) Confirmatory factor analysis of vulnerability to natural hazards: a household vulnerability assessment in Marinduque Island, Philippines. *Int J Disaster Risk Reduct* 50:101831. <https://doi.org/10.1016/j.ijdr.2020.101831>
- Prein AF, Gobiet A (2017) Impacts of uncertainties in European gridded precipitation observations on regional climate analysis. *Int J Climatol* 37:305–327. <https://doi.org/10.1002/joc.4706>

- Rabby YW, Hossain MB, Hasan MU (2019) Social vulnerability in the coastal region of Bangladesh: an investigation of social vulnerability index and scalar change effects. *Int J Disaster Risk Reduct* 41:101329. <https://doi.org/10.1016/j.ijdr.2019.101329>
- Rashetnia S, Jahanbani H (2021) Flood vulnerability assessment using a fuzzy rule-based index in Melbourne Australia. *Sustain Water Resour Manag* 7:13. <https://doi.org/10.1007/s40899-021-00489-w>
- Ravago M-LV, Mapa CDS, Aycardo AG, Abrigo MRM (2020) Localized disaster risk management index for the Philippines: is your municipality ready for the next disaster? *Int J Disaster Risk Reduct* 51:101913. <https://doi.org/10.1016/j.ijdr.2020.101913>
- Reckien D (2018) What is in an index? Construction method, data metric, and weighting scheme determine the outcome of composite social vulnerability indices in New York City. *Reg Environ Change* 18:1439–1451. <https://doi.org/10.1007/s10113-017-1273-7>
- Reyes C, Due E (2009) Fighting poverty with facts community-based monitoring systems. International Development Research Centre, Ottawa
- Reyes C, Mandap ABE, Quilitis JA et al (2017) The many faces of poverty:, vol 8. De La Salle University, Manila
- Rezaei F, Safavi HR, Ahmadi A (2013) Groundwater vulnerability assessment using fuzzy logic: a case study in the Zayandehrood Aquifers Iran. *Environ Manag* 51:267–277. <https://doi.org/10.1007/s00267-012-9960-0>
- Rossi G (2000) Drought Mitigation Measures: A Comprehensive Framework. In: Vogt JV, Somma F (eds) *Drought and drought mitigation in Europe*. Springer, Dordrecht, pp 233–246
- Rukmana D (2014) Vulnerable Populations. In: Michalos AC (ed) *Encyclopedia of quality of life and well-being research*. Springer, Dordrecht, pp 6989–6992
- Saha S, Kundu B, Paul GC et al (2021) Spatial assessment of drought vulnerability using fuzzy-analytical hierarchical process: a case study at the Indian state of Odisha. *Geomat Nat Haz Risk* 12:123–153. <https://doi.org/10.1080/19475705.2020.1861114>
- Salvacion AR (2020) Delineating soil erosion risk in Marinduque, Philippines using RUSLE. *GeoJournal* <https://doi.org/10.1007/s10708-020-10264-7>
- Salvacion AR (2016) Terrain characterization of small island using publicly available data and open-source software: a case study of Marinduque, Philippines. *Model Earth Syst Environ* 2:1–9. <https://doi.org/10.1007/s40808-016-0085-y>
- Salvacion AR (2018) Spatial pattern and determinants of village level poverty in Marinduque Island, Philippines. *GeoJournal* 85:257–267. <https://doi.org/10.1007/s10708-018-9944-6>
- Salvacion AR (2017) Exploring determinants of child malnutrition in Marinduque Island, Philippines. *Hum Ecol* 45:853–863. <https://doi.org/10.1007/s10745-017-9951-0>
- Salvacion AR (2022a) Chapter 11 - Multiscale drought hazard assessment in the Philippines. In: Pourghasemi HR (ed) *Computers in earth and environmental sciences*. Elsevier, pp 169–179
- Salvacion AR (2022b) Groundwater potential mapping using maximum entropy. In: Kumar P, Nigam GK, Sinha MK, Singh A (eds) *Water resources management and sustainability*. Springer Singapore
- Salvacion AR (2021) Mapping meteorological drought hazard in the Philippines using SPI and SPEI. *Spat Inf Res*. <https://doi.org/10.1007/s41324-021-00402-9>
- Salvacion AR, Magcale-Macandog DB (2015) Spatial analysis of human population distribution and growth in Marinduque Island, Philippines. *J Mar Isl Cult* 4:27–33. <https://doi.org/10.1016/j.imic.2015.06.003>
- Salvacion AR, Magcale-Macandog DB, Cruz PCSta, et al (2018) Evaluation and spatial downscaling of CRU TS precipitation data in the Philippines. *Model Earth Syst Environ* 4:891–898. <https://doi.org/10.1007/s40808-018-0477-2>
- Salvador C, Nieto R, Linares C et al (2021) Drought effects on specific-cause mortality in Lisbon from 1983 to 2016: risks assessment by gender and age groups. *Sci Total Environ*. <https://doi.org/10.1016/j.scitotenv.2020.142332>
- Santos JF, Portela MM, Pulido-Calvo I (2011) Regional frequency analysis of droughts in Portugal. *Water Resour Manage* 25:3537. <https://doi.org/10.1007/s11269-011-9869-z>
- Schwalm CR, Anderegg WRL, Michalak AM et al (2017) Global patterns of drought recovery. *Nature* 548:202–205. <https://doi.org/10.1038/nature23021>
- Senay GB, Velpuri NM, Bohms S, et al (2015) Chapter 9: Drought monitoring and assessment: remote sensing and modeling approaches for the famine early warning systems network. In: Baldassarre JFSPD (ed) *Hydro-meteorological hazards, risks and disasters*. Elsevier, Boston, pp 233–262
- Shahid S, Behrawan H (2008) Drought risk assessment in the western part of Bangladesh. *Nat Hazards* 46:391–413. <https://doi.org/10.1007/s11069-007-9191-5>

- Sharafi L, Zarafshani K, Keshavarz M et al (2020) Drought risk assessment: towards drought early warning system and sustainable environment in western Iran. *Ecol Ind* 114:106276. <https://doi.org/10.1016/j.ecolind.2020.106276>
- Singh GR, Jain MK, Gupta V (2019) Spatiotemporal assessment of drought hazard, vulnerability and risk in the Krishna River basin, India. *Nat Hazards* 99:611–635. <https://doi.org/10.1007/s11069-019-03762-6>
- Spinoni J, Barbosa P, De Jager A et al (2019) A new global database of meteorological drought events from 1951 to 2016. *J Hydrol: Reg Stud* 22:100593. <https://doi.org/10.1016/j.ejrh.2019.100593>
- Spinoni J, Naumann G, Carrao H et al (2014) World drought frequency, duration, and severity for 1951–2010. *Int J Climatol* 34:2792–2804. <https://doi.org/10.1002/joc.3875>
- Suryabagavan KV (2017) GIS-based climate variability and drought characterization in Ethiopia over three decades. *Weather Clim Extrem* 15:11–23. <https://doi.org/10.1016/j.wace.2016.11.005>
- Thapa R, Gupta S, Guin S, Kaur H (2017) Assessment of groundwater potential zones using multi-influencing factor (MIF) and GIS: a case study from Birbhum district, West Bengal. *Appl Water Sci* 7:4117–4131. <https://doi.org/10.1007/s13201-017-0571-z>
- Tibesigwa B, Visser M, Collinson M, Twine W (2016) Investigating the sensitivity of household food security to agriculture-related shocks and the implication of social and natural capital. *Sustain Sci* 11:193–214. <https://doi.org/10.1007/s11625-015-0332-6>
- Tirivarombo S, Osupile D, Eliasson P (2018) Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). *Phys Chem Earth Parts a/b/c* 106:1–10. <https://doi.org/10.1016/j.pce.2018.07.001>
- Touma D, Ashfaq M, Nayak MA et al (2015) A multi-model and multi-index evaluation of drought characteristics in the 21st century. *J Hydrol* 526:196–207. <https://doi.org/10.1016/j.jhydrol.2014.12.011>
- Twinomuhangi R, Sseviiri H, Mulinde C et al (2021) Perceptions and vulnerability to climate change among the urban poor in Kampala City Uganda. *Reg Environ Change*. <https://doi.org/10.1007/s10113-021-01771-5>
- Vicente-Serrano SM, Beguería S, López-Moreno JJ (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J Clim* 23:1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>
- Wang R, Zhang J, Wang C, Guo E (2020) Characteristic analysis of droughts and waterlogging events for maize based on a new comprehensive index through coupling of multisource data in Midwestern Jilin Province. *China Remote Sens* 12:60. <https://doi.org/10.3390/rs12010060>
- Wilhite DA (2000) Drought: a global assessment. Routledge, London
- World Meteorological Organization (2012) Standardized precipitation index user guide. World Meteorological Organization, Geneva, Switzerland
- Wu B, Ma Z, Yan N (2020) Agricultural drought mitigating indices derived from the changes in drought characteristics. *Remote Sens Environ* 244:111813. <https://doi.org/10.1016/j.rse.2020.111813>
- Xie P, Lei X, Zhang Y et al (2018) Cluster analysis of drought variation and its mutation characteristics in Xinjiang province, during 1961–2015. *Hydrol Res* 49:1016–1027. <https://doi.org/10.2166/nh.2018.105>
- Xu B, Hicke JA, Abatzoglou JT (2019) Drought and moisture availability and recent western spruce budworm outbreaks in the Western United States. *Forests* 10:354. <https://doi.org/10.3390/f10040354>
- Yang T-H, Liu W-C (2020) A general overview of the risk-reduction strategies for floods and droughts. *Sustainability* 12:2687. <https://doi.org/10.3390/su12072687>
- Yoon DK (2012) Assessment of social vulnerability to natural disasters: a comparative study. *Nat Hazards* 63:823–843. <https://doi.org/10.1007/s11069-012-0189-2>
- Zadeh LA (1965) Fuzzy sets. *Inf Control* 8:338–353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- Zhang J (2004) Risk assessment of drought disaster in the maize-growing region of Songliao Plain, China. *Agr Ecosyst Environ* 102:133–153. <https://doi.org/10.1016/j.agee.2003.08.003>
- Zhao Y, Lu Z, Wei Y (2019) An assessment of global precipitation and evapotranspiration products for regional applications. *Remote Sens*. <https://doi.org/10.3390/rs11091077>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.