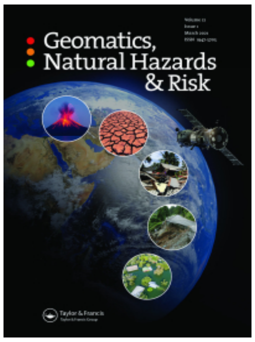

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RESEARCH ARTICLE

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Spatial and temporal changes of social flood vulnerability in municipalities of Slovakia

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ABSTRACT

Social flood vulnerability analysis is an inevitable task for effective flood risk assessment and management, as it defines the sensitivity, resistance, and resilience of people, households, and communities against floods. This study aimed to assess the spatial and temporal changes in social flood vulnerability between 2001, 2011, and 2021. A place-based (municipalities) and hazard-independent approach was used to calculate the social flood vulnerability index (SFVI) in the studied years using geographic information systems (GIS) and spatial–statistical methods. The interdependencies among the eight selected indicators were studied based on principal component analysis and factor analysis, whereas variance analysis was used to analyze the changes in each of the indicators as well as in the SFVI within the studied years. Spatial clusters of indicators and SFVI were determined using the spatial autocorrelation. Based on the results, the highest values of SFVI in each of the studied years were recorded in southern and eastern Slovakia, and overall, it showed an increasing trend throughout the study period. The changes in SFVI and almost all indicators, except population density, were statistically significant between the studied years. The results of this study are of practical importance for integrated flood risk management at a national scale.

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Flood vulnerability; municipality; principal component analysis; variance analysis; spatial autocorrelation

1 Introduction

The concept of flood vulnerability is based on the idea that flood damage is a function of flood magnitude and the vulnerability of physical, social, economic, environmental, and institutional systems (Morrow 1999; Turner et al. 2003; Adger et al. 2004; Wisner et al. 2004; Nasiri et al. 2016). Vulnerability represents the inherent characteristics of a system that creates the potential for harm and can be defined independently of the probability of flood hazard occurrence (Sarewitz et al. 2003). According to Solín and Skubinčan (2013), attributes that express the inherent predisposition of physical, economic, social, environmental, and institutional systems to damage or loss form the basis of the concept of sensitivity. The social dimension of vulnerability is embedded in terms of resistance and resilience, which characterize a person or group in terms of its ability to anticipate, cope with, resist, and recover from the negative impact of the flood (Blaikie et al. 1994; Vis et al. 2003; McClymont et al. 2020).

Under the multidimensional concept, flood risk consists of three components: the probability of flood discharge occurrence related to different return periods and the consequences associated with the specific flood event, which are conveyed via the components of exposure and vulnerability. In this sense, flood risk is represented by the expected economic and environmental losses or loss of life caused by the flood hazard, that is, flood risk is expressed as a product of hazard, exposure, and vulnerability (Adger 2006; Koks et al. 2015).

Following the more recent perspectives on the concept of vulnerability, we distinguish between five main dimensions of vulnerability: physical, social, economic, environmental, and institutional (Scheuer et al. 2011;

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Birkmann et al. 2013; Rasool et al. 2024). The physical dimension refers to potential for damage to physical assets, such as built-up areas, infrastructure or open spaces (Birkmann et al. 2013). Social vulnerability is represented by a society made up of individuals, households, communities, and even nations, with existing inequalities between them. Economic vulnerability is mainly defined by potential damage (direct or indirect) to buildings and their equipment, industrial facilities, crops, infrastructure, etc. (Sieg et al. 2019). Environmental vulnerability refers to the degradation of the ecosystem as a whole (Messner et al. 2007). Institutional vulnerability focuses on the potential for damage to governance systems, organizational form and function as well as guiding legal and informal rules (Birkmann et al. 2013).

Vulnerability is most often assessed either at the level of an individual, household, or differently defined group, when it concerns so-called social-based vulnerability (Morrow 1999; Karagiorgos et al. 2016; Solín et al. 2018), or at the level of place (so-called place-based vulnerability), which is spatially defined, such as municipalities, counties, regions, or is expressed through a grid (Cutter et al. 2003). Vulnerability mapping and assessment approaches can be divided into two types: hazard independent and hazard dependent.

The hazard-independent approach expresses the sensitivity of the social, economic, and environmental systems to flood damage, their ability to cope with floods, and their ability to recover after a flood independently of the flood hazard, that is, the probability of the occurrence of a flood situation (Adger et al. 2004). The methods of this vulnerability assessment approach focus on establishing indices that are calculated through indicators, also called proxy variables, related to social, economic, or environmental systems (Solín 2012; Vojtek and Moradi 2024). Indicators are either selected subjectively based on a logically justified dependence between them and the negative effects of the flood (Tapsell et al. 2002; Pathak et al. 2020) or more objectively by reducing a large number of indicators to a few statistically significant (main) variables using statistical methods (Cutter et al. 2003).

The hazard-dependent approach relies on flood hazard, which is defined most often by the extent of flooding, flow depth, or velocity (Kreibich et al. 2009). This approach is primarily used to assess economic vulnerability, that is, expected flood damage to property or infrastructure, which is expressed monetarily, most often via absolute or relative stage-damage curves (Merz et al. 2004; Kang et al. 2005; Thieken et al. 2005; Middelmann-Fernandes 2010; Zeleňáková et al. 2018).

Indicators representing social vulnerability mainly refer to the demographic or socioeconomic characteristics of individuals or households, such as gender, age, health status, income, employment, and education (Hinojos et al. 2023). All these indicators change in space and time and, therefore, may play different roles in the calculation of social vulnerability indices (Nguyen et al. 2021; Tang et al. 2021). Determining the drivers of change in social vulnerability indices is crucial for flood managers or urban planners to define strategies and measures to reduce vulnerability to floods (Mohanty et al. 2020). However, vulnerability assessment is often omitted from flood risk assessments, even in the case of the official Preliminary Flood Risk Assessment (PFRA) or the creation of flood risk maps in Slovakia under the EU Floods Directive (2007).

At global scale, the research on spatial and temporal changes in flood vulnerability points out both increasing and decreasing trends depending on different countries (Tanoue et al. 2016). However, as reported by Rogers et al. (2025), urban areas are especially vulnerable in nearly all global regions, and they are expected to see a 33% increase in population exposure. Sauer et al. (2024) found out that vulnerability is significantly lower in areas with good structural characteristics and significantly higher in low developed areas. They stated that socioeconomic development during the studied period 2000–2018 was not able to reduce the vulnerability. A recent study by Paprotny et al. (2025) compared the development of flood vulnerability at the European level between 1950 and 2020. They found out that western European countries have relatively high vulnerability while the lowest values were recorded in central and northern Europe. A significant decline in flood vulnerability during 1950 and 2020 was recorded for all three studied indicators of fatalities, people affected, and economic losses, which was attributed to improved flood adaptation and protection.

The global or European scale research on changes in flood vulnerability also underscores the need for more precise assessments on more detailed scales, such as the national scale. However, at the national scale of Slovakia, studies on mapping and assessing spatio-temporal variations in flood vulnerability among Slovakia's municipalities are still lacking. There are no studies conducted for municipal scale in Slovakia, which would assess spatial and temporal changes in (social) or other dimension of flood vulnerability.

There are very few studies assessing flood vulnerability at the municipal level in Slovakia, but only for a particular year. In particular, Solín (2012) and Solín et al. (2014) analyzed the social and economic flood vulnerability in municipalities located in headwater basins of Slovakia using the census data from 2001. Moreover, Solín (2025) assessed vulnerability of Roma settlements in Slovakia using the Atlas of Roma Communities from 2019. Using the municipality level for flood vulnerability assessment is based on the fact that each municipality can influence different aspects of flood prevention, mitigation, protection, or adaptation by managing its own territory and can use several tools for this purpose, such as spatial plans, grants for technical and non-technical flood control measures, and the involvement of local residents and stakeholders in flood risk management (Vojtek et al. 2022, 2023b). The advantage is also the effective use of the results by the authorities responsible for national flood risk management and its use in the periodic updating of the PFRA and flood maps under the EU Floods Directive (2007) (Vojtek and Vojteková 2018).

Some recent studies have used principal component analysis (PCA) to study (social) vulnerability to floods at certain administrative scales, such as municipalities, census tracts or other types of administrative units. For instance, Wu (2021) assessed the vulnerability, including the social component, with the use of PCA for 256 coastal census tracts and 24 municipalities along the coast of Connecticut, U.S.A. Arunachalam et al. (2023) mapped social vulnerability to hazards, including floods, using the PCA and factor analysis for different administrative units in Chennai metropolitan area, India. Using PCA, Ajtai et al. (2023) analyzed social flood vulnerability for local administrative units (LAUs) from the Someș-Tisa River Basin (Romania), which is located in flooded areas. Bucherie et al. (2022) compared social vulnerability indices using the PCA and expert knowledge in the case of Ecuadorian administrative level 3. Abdrabo et al. (2023) mapped flood vulnerability in 101 neighbourhoods of Alexandria city in Egypt. However, it has to be noted that none of these studies focused on the spatial distribution of social vulnerability to floods over time.

Therefore, based on the theoretical background presented in this section, the aim of this study was to assess the spatial and temporal changes in social flood vulnerability between 2001, 2011, and 2021 using geographic information systems (GIS) and spatial-statistical methods. We used place-based (municipal level) and hazard-independent approach to create the social flood vulnerability index (SFVI) and individual studied years. Furthermore, we followed four partial objectives:

- To analyze the interdependencies among the eight selected indicators using principal component analysis (PCA) and factor analysis.
- To analyze the changes in each of the eight vulnerability indicators within the individual studied years using variance analysis.
- To analyze the changes in the SFVI for the individual studied years using variance analysis.
- To analyze the spatial dependence (clusters) among municipalities for individual vulnerability indicators as well as the final SFVI for each studied year using the spatial autocorrelation.

2 Study area

The study area was represented by 2927 municipalities in Slovakia. The total area of Slovakia is 49,034 km^2 and the total population is 5,424,687 inhabitants as of 31 December 2023. The municipal level corresponds to LAU 2 – local administrative units (NUTS 5) based on the Nomenclature of Territorial Units for Statistics (NUTS). The study area, represented by 2927 municipalities, is shown in Figure 1. Regarding Figure 1, the data source for individual types of boundaries and regional cities within Slovakia are the vector (shapefile) layers available through the Geodetic and Cartographic Institute. In case of the smaller map of European countries in the left corner, the source is the free ArcGIS vector layers. The geomorphological units of Slovakia belong to the Alpine-Himalayan System, particularly the Carpathian subsystem of mountainous relief and the Pannonian Basin subsystem composed of lowlands and low-lying basins. The elevation difference in Slovakia is 2561 m. Lapin et al. (2002) defined three climatic regions in Slovakia: warm, moderately warm, and cool. Most Slovak rivers belong to the Danube River Basin, which

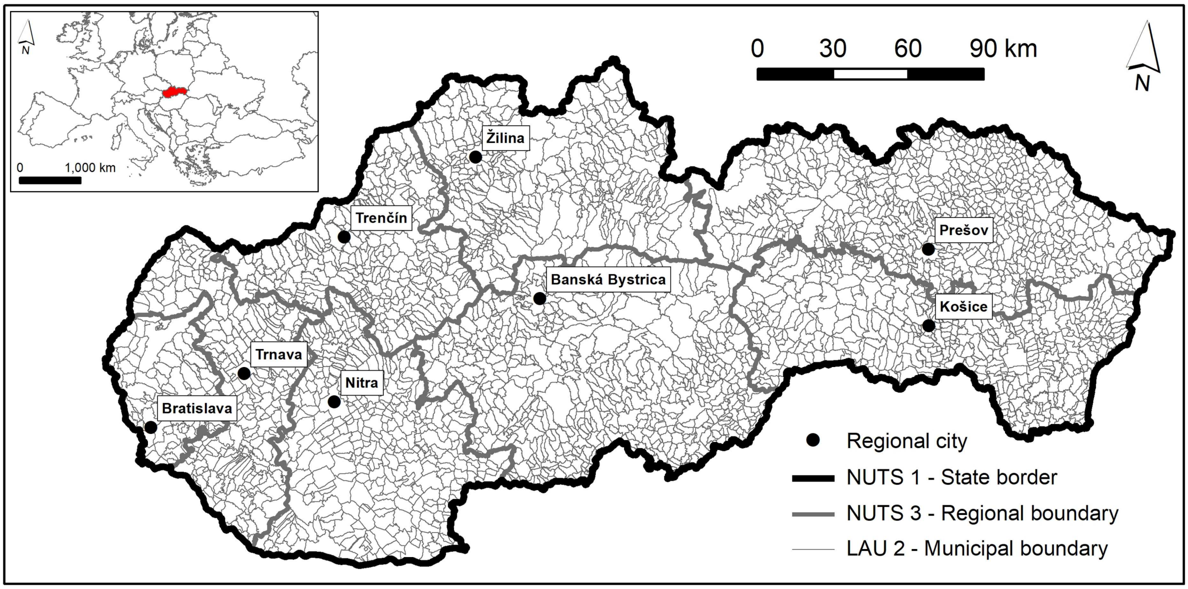

Figure 1. Study area consisting of 2927 municipalities in Slovakia.

drains approximately 96% of all water into the Black Sea. The rest of the water is drained by the Poprad and Dunajec rivers, which are tributaries of the Vistula River in Poland. Three types of runoff regimes are characteristic of rivers in Slovakia: temporary snow, combined snow-rain, and rain-snow (Šimo and Zaťko 2002).

Regarding flood risk management and the implementation of the EU Floods Directive (2007) in Slovakia, it has to be noted that three cycles of the Preliminary Flood Risk Assessment (PFRA, 2011, 2018, 2024), two cycles of flood hazard and risk maps (2015, 2023), and flood risk management plans (2015, 2021) have already been published. However, the PFRA has not addressed the vulnerability component in any of the three cycles, either on municipal or basin (sub-basin) scale. This is considered a shortcoming of the national PFRA since demographic, social, and other types of data concerning population characteristics are readily available for municipal-scale assessments.

3 Data and methods

3.1 Processing of indicators

We selected eight indicators representing social vulnerability based on data availability, literature review, and expert judgment. These indicators correspond to the main attributes of vulnerability (sensitivity/resistance/resilience). In particular, we used the following indicators: population density of municipalities; share of residents aged 65+ from the total number of residents; share of unemployed residents from the total number of economically active residents; share of the Roma ethnicity from the total number of residents; share of households with six or more persons from the total number of households; share of incomplete households from the total number of households; share of residents without education and with primary education from the total number of residents; and share of disabled residents from the total number of residents.

Population density is a common vulnerability indicator chosen for the calculation of SFVI (Isia et al. 2023; Roldán-Valcarce et al., 2023). The population in the age category over 65 years was chosen because it represents one of the most vulnerable age categories due to generally lower physical strength and mobility, and the majority of them are already retired and may live alone (El-Zein et al. 2021). For the unemployed population, their vulnerability is generally high because of their very low or no income and possible problems recovering from a flood event (Chakraborty et al. 2020). The Roma ethnicity indicator was selected because of several concerns that raise the vulnerability of this ethnicity. It is mainly the construction of colonies near water streams, poor quality dwellings (huts or shacks), and overcrowding (Solín 2012; Vojtek 2023). The indicator of households with six or more persons was chosen because of possible financial problems when taking care of more persons and the inability to resist and recover from flooding appropriately (El-Zein et al. 2021; Ingle and Chattaopadhyay 2022). Similarly, incomplete households are more vulnerable, as only one parent takes care of children and has possible financial problems (Solín 2012). Indicators representing the disabled population are common in the literature, and this group of people with physical disabilities is perceived as more vulnerable to flooding (Chakraborty et al. 2020; Isia et al. 2023).

All indicators were processed in spreadsheets and into vector GIS layers using the Microsoft Excel and ArcGIS software (version 10.2.2). Source data were retrieved from the DATAcube database (https://datacube.statistics.sk) or from the national population census for 2001, 2011, and 2021 provided by the Statistical Office of the Slovak Republic. Most of the indicators contained percentage values, except for population density, which represents the population per km^2. To obtain all the data at the same scale, we used their normalization to the range [0, 1] based on the maximum method (Equation (1)) (Vojtek et al. 2024):

$$x_j' = \frac{x_j}{\max(x_j)}, \tag{1}$$

where x'_j is the normalized scaled value of the j-th indicator, x_j is the original value of the j-th indicator, and $\max(x_j)$ is the original maximum value of the j-th indicator. The statistical analyses, i.e. PCA, factor analysis, and variance analysis described in subsections 3.3 and 3.4, were performed using the STATISTICA software (version 10).

3.2 Multicolinearity test

Multicollinearity analysis is an important task for quantifying the degree of correlation between independent variables. Multicollinearity can be a problem when calculating the vulnerability index because it distorts the statistical significance of the independent variable. When variables are highly correlated, it may no longer be possible to determine which influence comes from which variable. To study multicollinearity among the chosen indicators, we used the variance inflation factor (VIF) index (Vojtek et al., 2023a, 2025). The higher the VIF value is, the greater the chance of multicollinearity. In general, values above 10 are considered critical. Therefore, the VIF value increases with increasing multicollinearity. The acceptable limit of the VIF index is below 5. A VIF result close to 1 indicates no correlation. Equation (2) was used to calculate the VIF index:

$$\mathrm{VIF} = \frac{1}{1 - R^2}, \tag{2}$$

where R^2 is the coefficient of determination of the variable (Tamura et al. 2019).

3.3 PCA and factor analysis

Principal component analysis (PCA) is a linear dimensionality reduction used for data analysis, which is linearly transformed into a new coordinate system, where the directions (principal components) capturing the largest variation in the data are identified. Several methods can be used to determine the number of principal components to be maintained. In this study, we used a scree plot and eigenvalues lying approximately on a straight line. First, we calculated the Pearson–Bravais correlation coefficient, then the eigenvalues of the correlation matrix, and the percentage of total variance explained by individual principal components (Jolliffe and Cadima 2016).

Based on PCA, which is a widely used method for factor extraction, we applied a factor analysis. Factor analysis is a statistical method for defining the variability among variables in terms of a potentially lower number of unobserved variables called factors. Factor analysis aims to find joint variations in response to unobserved latent variables, that is, factor analysis may be considered a special case of errors-in-variables models or measurement error models that account for measurement errors in the independent variables

(Jöreskog 1983). The result of the factor analysis was a matrix of factor saturations. It is a matrix of correlation coefficients between the indicators and factors. A high factor saturation means that the factor significantly affects the indicator (variable), and the indicator significantly affects the factor. In this study, we use the rule that those factors with absolute values higher than 0.3 are considered statistically significant, factors with an absolute value greater than 0.4 are considered moderately significant, and values of factor saturation whose absolute value is greater than 0.5 are considered very significant (Markechová et al. 1990).

We obtained the initial information for factor analysis from the correlation matrix and then calculated the eigenvalues of the implemented correlation matrix. According to the Kaiser criterion, the number of factors chosen should be equal to the number of eigenvalues of the realization of the matrix, which are greater than 1. Furthermore, we calculated the matrix of the rotated factor loadings using varimax rotation.

3.4 Variance analysis of indicators

In the variance analysis, we first calculated the arithmetic means for each indicator in 2001, 2011, and 2021. Based on the one-factor analysis of variance for an unbalanced model, we verified which of the differences in arithmetic means were statistically significant. We tested the null hypothesis that all arithmetic means are equal to the alternative hypothesis; not all arithmetic means are equal. If the calculated p-value is sufficiently small ($p < 0.05$ or $p < 0.01$), we reject the tested null hypothesis about the equality of the arithmetic means of the studied indicator (at the significance level of 0.05 or 0.01). Otherwise, we cannot reject the null hypothesis; that is, the differences in arithmetic means are not statistically significant (Markechová et al. 1990).

Furthermore, we studied which years differed with respect to the mean value of the individual indicators. When comparing the differences between individual years in the variance analysis, we used Scheffe's post hoc test and the corresponding p-value. The same procedure, as described in this subsection, was applied to the SFVI in the studied years.

3.5 Determination of the SFVI

The final SFVI was calculated as an aggregation of the eight social vulnerability indicators, which were assigned an equal weight of 1/8, based on Equation (3):

$$SFVI = \sum_{j} x'_j \frac{1}{8} \tag{3}$$

where $SFVI$ is the social flood vulnerability index and x'_j is the j-th indicator in the range [0, 1]. Thus, we treated each indicator as equally important for calculating the SFVI. This procedure was applied to each study year (2001, 2011, and 2021).

Furthermore, the final SFVI for each year was correlated (Pearson correlation) with the number of flood events in municipalities for the corresponding 10-year periods before the study year: 1992–2001, 2002–2011, and 2012–2021. The database of flood events was created based on Reports on the Course and Consequences of Floods in the Slovak Republic available from 2001 on the website of the Ministry of Environment of the Slovak Republic (ME SR) and (ii) documents of the PFRA (2011, 2018, 2024) available on the website of the ME SR.

3.6 Spatial clusters of indicators and SFVI

To determine the spatial patterns (clusters) for individual indicators as well as the final SFVI in the studied years, we used the local Moran's coefficient of spatial autocorrelation (Moran 1950; Anselin 1995). Using this method in ArcGIS software (version 10.2.2), we aimed to identify neighbouring spatial units (municipalities) with similar values or vice versa, i.e. municipalities with values that are different from their neighbours.

The obtained local Moran's coefficients of spatial autocorrelation were tested in terms of their statistical significance. We calculated the z-scores, which were then compared to the p-values. The closer the value of z-score is to 1, the higher the level of confidence that the indicators or SFVI are spatially autocorrelated. If the p-value is less than 0.05 or 0.01, the null hypothesis that there is no spatial autocorrelation among the values of indicators or SFVI in n spatial units is rejected at one of these significance levels. If the p-value is greater than 0.05 or 0.01, the null hypothesis cannot be rejected.

Furthermore, we used the site-specific local indicators of spatial association (LISA), where the sum of all LISA indicators is proportional to the global value of Moran's statistics (Anselin 1995). The results of the local Moran's coefficients of spatial autocorrelation were visualized by the Moran's scatter plots, which were created in GeoDa software (version 1.20.0.20) (Anselin 1996), as well as in the form of maps showing spatial dependence (high–high/hot spots, low–low/cold spots, low–high/spatial outliers or high–low/spatial outliers) among municipalities in regard to individual indicators and the SFVI in the studied years.

4 Results

4.1 Spatial and temporal changes in vulnerability indicators

Figure 2 shows the normalized values of the population density for the individual studied years. As we can see, the highest density is mainly in regional cities, such as Bratislava, Trnava, Žilina, Prešov, or Košice, or district towns, such as Prievidza or Poprad. Overall, the population density slightly increased throughout the years based on average values of 0.007, 0.008, and 0.009, which correspond to the years 2001, 2011, and 2021, respectively. Figure 3 depicts the population development over 65 years in the municipalities. We can see continuous aging of Slovakia's population from 2001 to 2021, which is also confirmed by the increasing average values from 0.170 (2001), 0.257 (2011), and 0.341 (2021). The highest normalized values were recorded mostly in western and central Slovakia, where natality was also lower compared to regions of eastern or northern Slovakia. Figure 4 shows the normalized values of the unemployed population, that is, the share of unemployed persons in the economically active population. Overall, the unemployment rate has a decreasing trend throughout the years, which is also documented by decreasing average values of 0.260, 0.224, and 0.112 for 2001, 2011, and 2021, respectively. However, municipalities with the highest share of the unemployed population remain more or less throughout the years and are located mainly in eastern and southern Slovakia.

Figure 5 shows the situation with the share of Roma ethnicity, which is similar to the share of the unemployed population, as a large portion of this ethnicity has been unemployed for a long period. The municipalities with the highest shares are located mainly in the eastern, southern, and central parts of Slovakia. A very low share of Roma ethnicity can be seen, especially in Western Slovakia. Based on the average values, the Roma population slightly increased from 2001 to 2011, but in 2021, we recorded a decrease, which can be explained by not providing true answers during the last population census about nationality or not returning the census questionnaire. Figure 6 shows the development of households with six or more people. As we can see, the overall values of this indicator increased throughout the years 2001, 2011, and 2021, which is also documented by the average values of 0.168, 0.188, and 0.297, respectively. The municipalities with the highest normalized values of this indicator are located mainly in northern and eastern Slovakia, which are regions with higher natality than the rest of Slovakia. Figure 7 shows the increase in the normalized values of incomplete households throughout the years 2001, 2011, and 2021, which are also documented by the average values of 0.227, 0.263, and 0.272, respectively. However, the spatial patterns were quite different in individual years. For instance, in 2011, higher values were observed in western Slovakia, while in 2021, higher values were observed in southern and central Slovakia. The development of normalized values for the disabled population in the municipalities of Slovakia is shown in Figure 8. As we can see, the average value slightly decreased from 0.165 in 2001 to 0.159 in 2011. However, there was an increase in the average value of 0.181 by 2021. The municipalities with the highest values are mostly concentrated in central or southern Slovakia each year. Figure 9 shows the population without education or with only a primary education. The average value of this indicator increased from 2001 (0.295) to 2011 (0.365) but decreased by 2021 (0.306). The highest values throughout the years were recorded in municipalities in southern and eastern Slovakia.

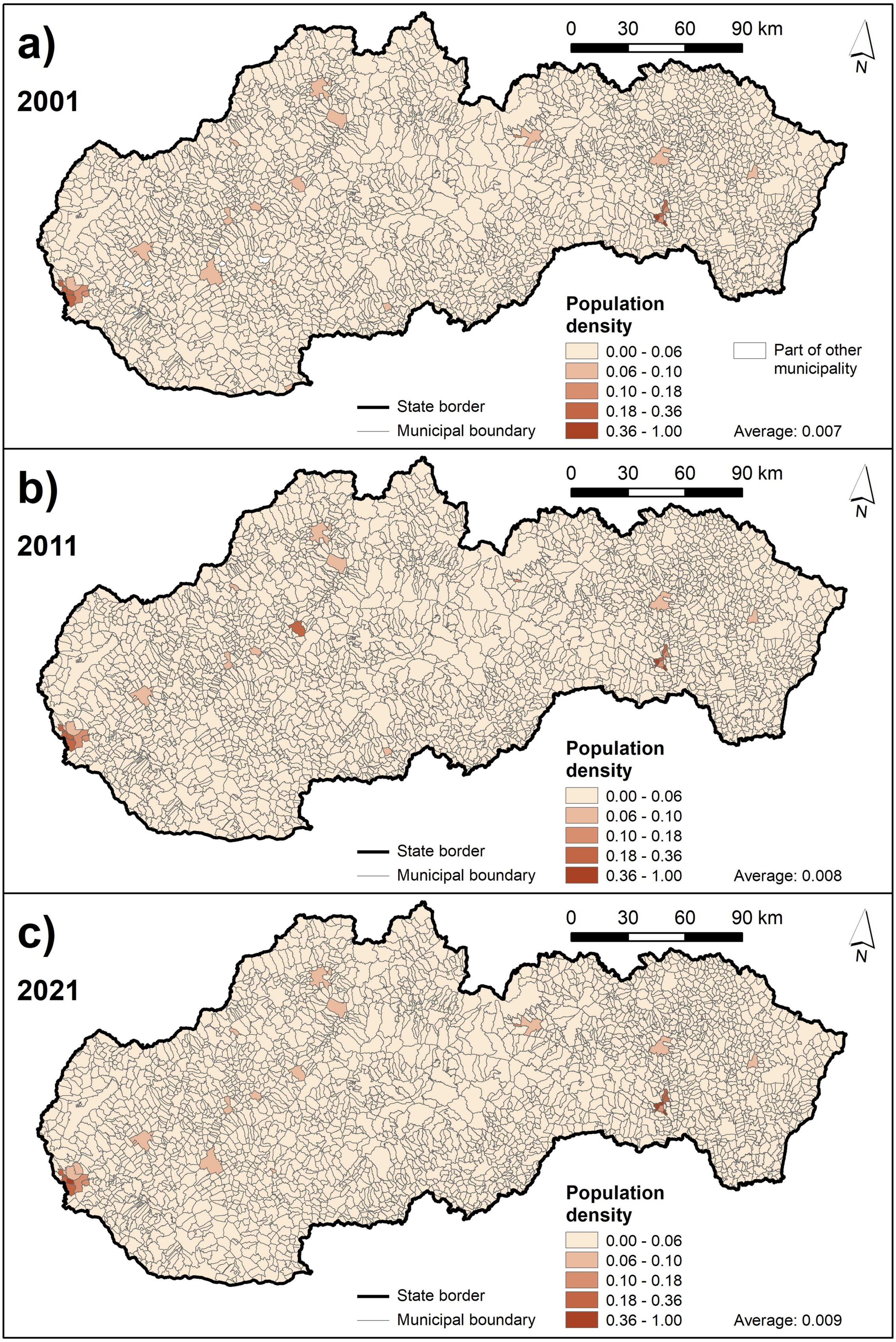

Figure 2. Normalized values of population density in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

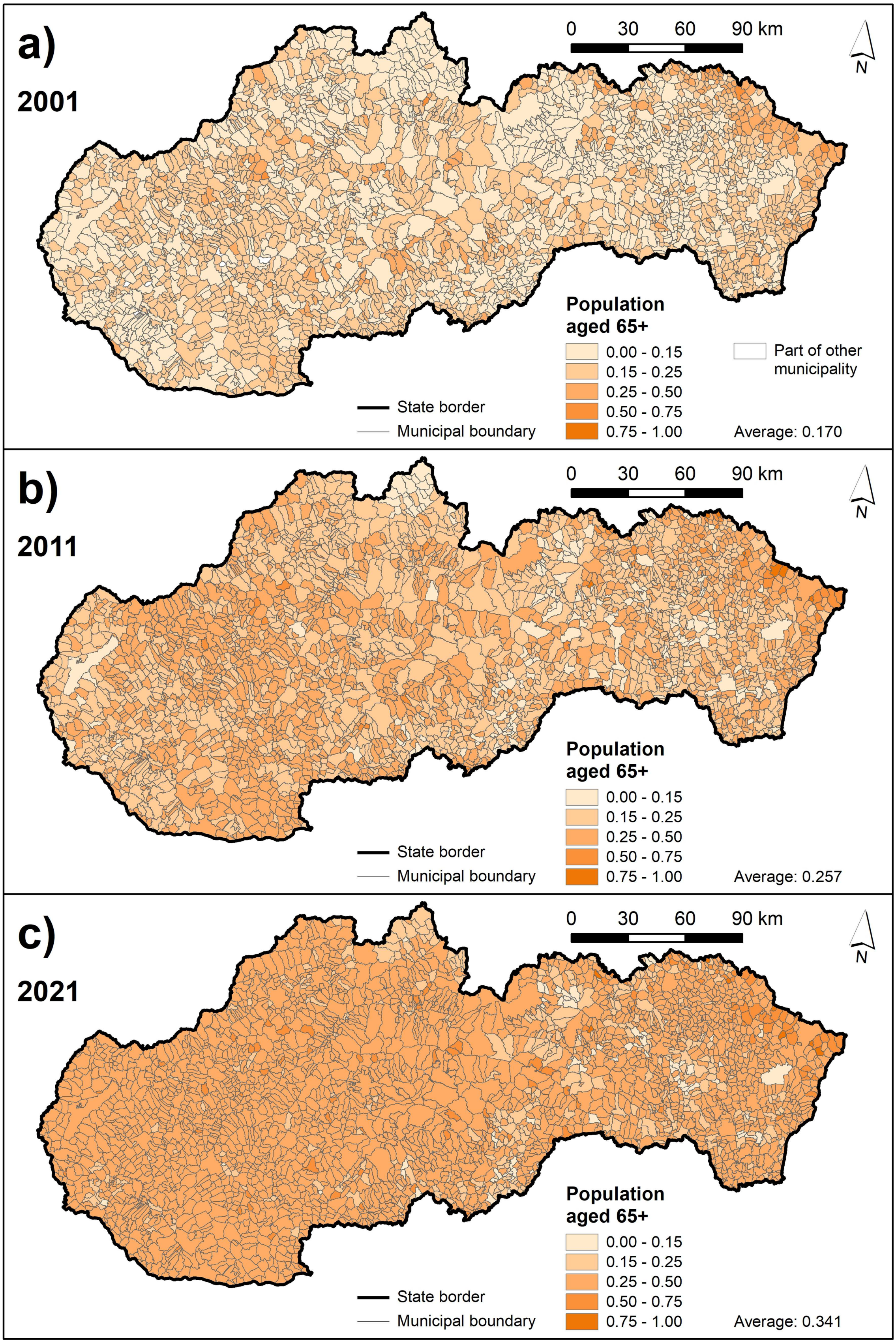

Figure 3. Normalized values of population aged 65+ in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

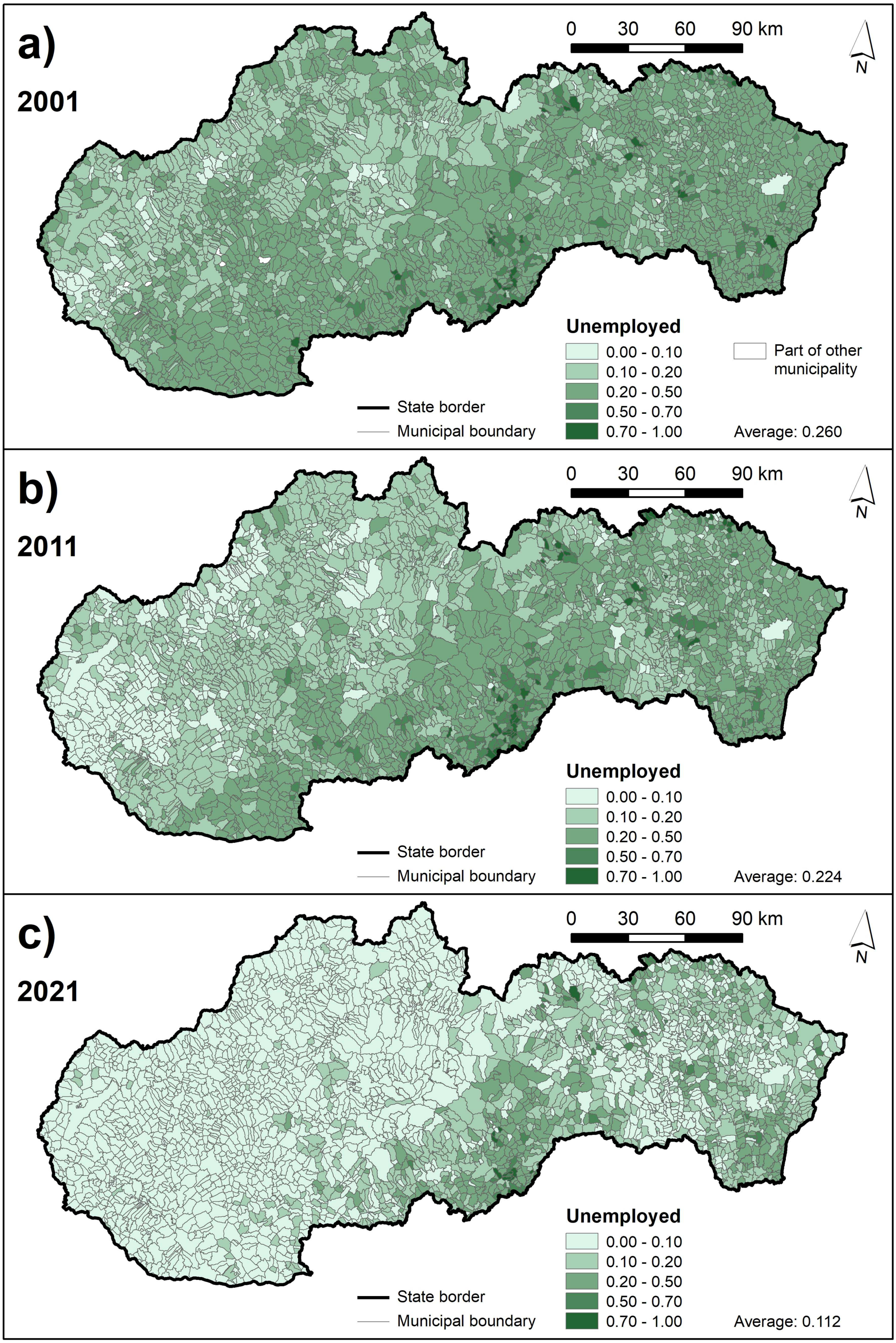

Figure 4. Normalized values of unemployed population in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

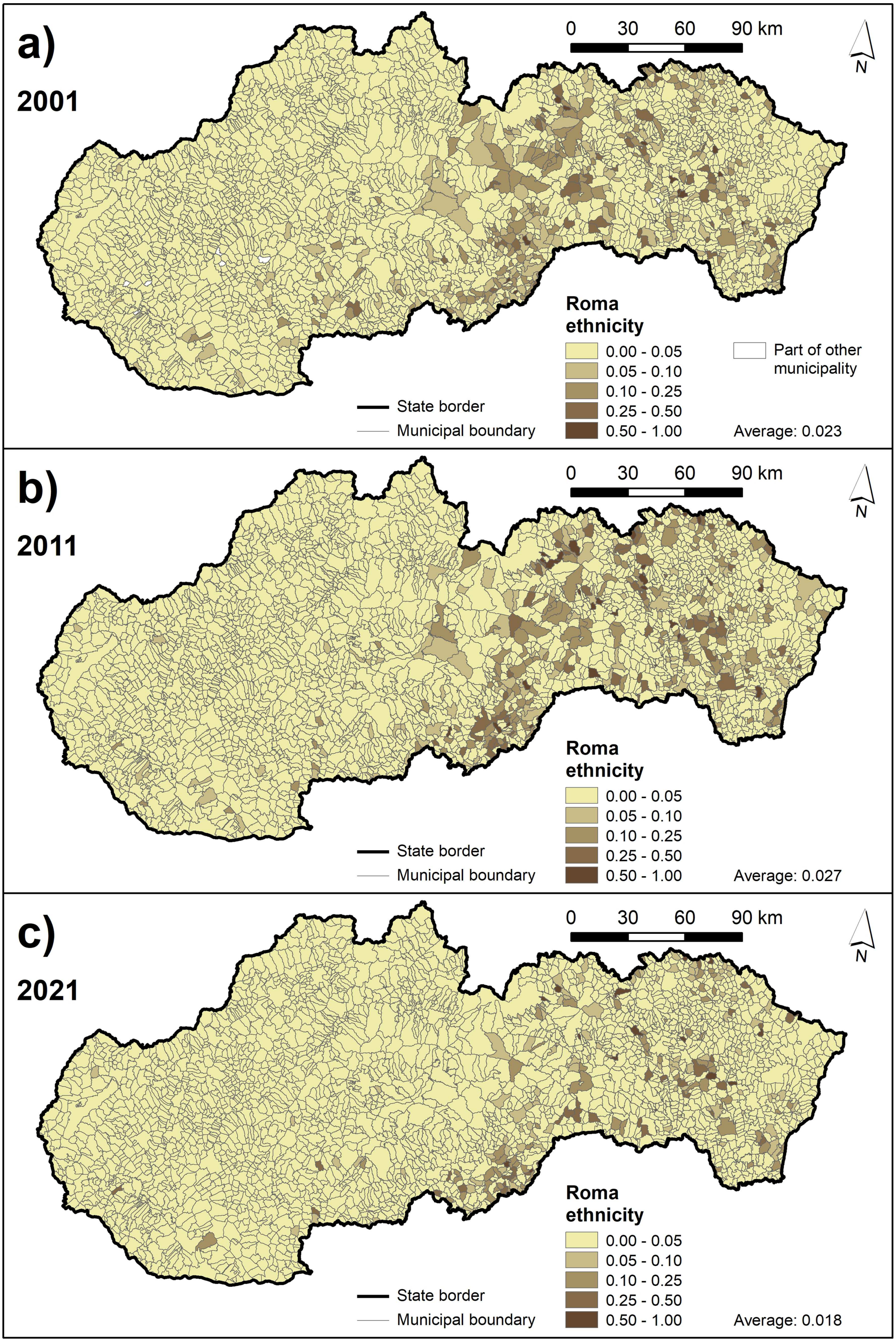

Figure 5. Normalized values of Roma ethnicity in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

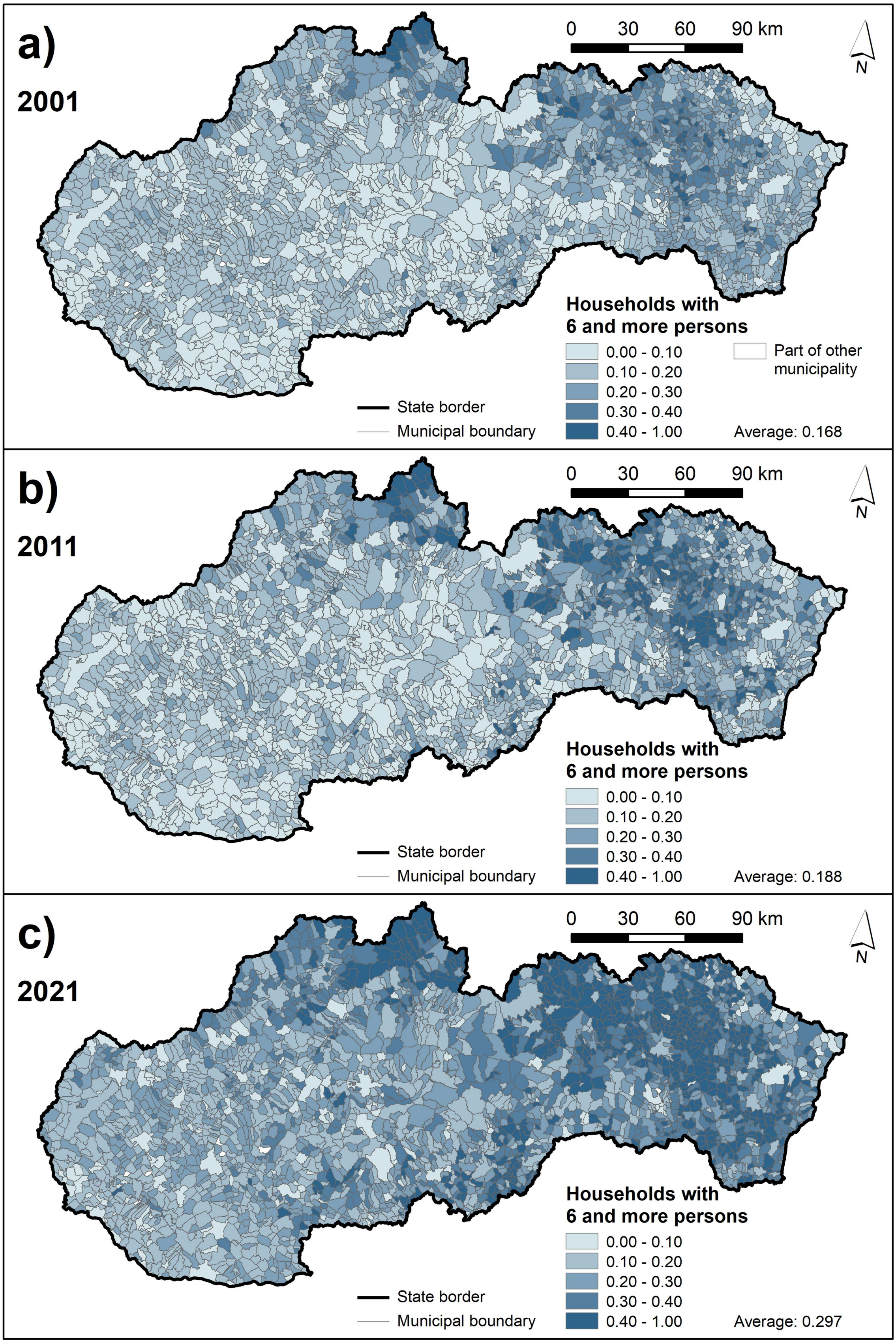

Figure 6. Normalized values of households with six and more persons in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

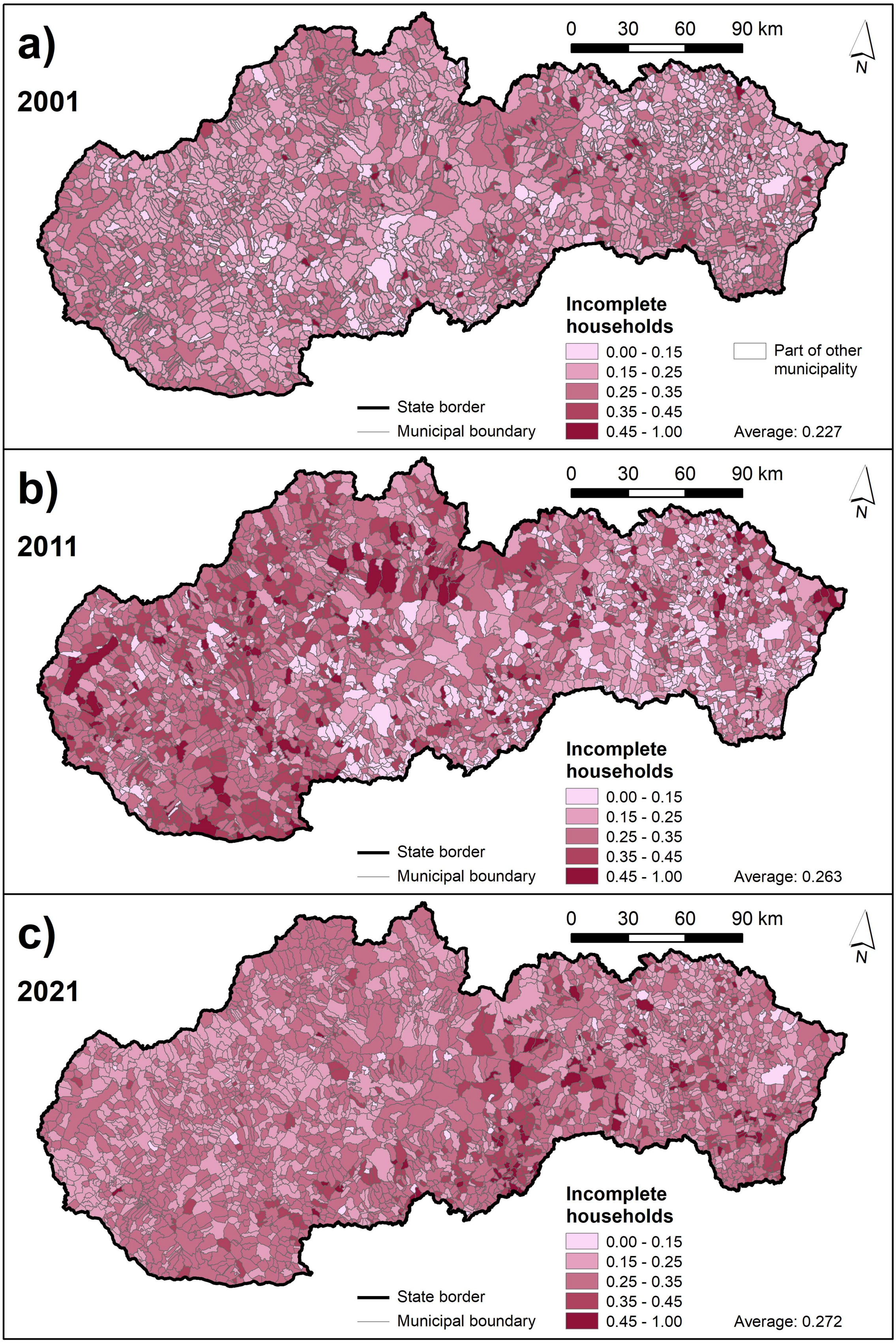

Figure 7. Normalized values of incomplete households in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

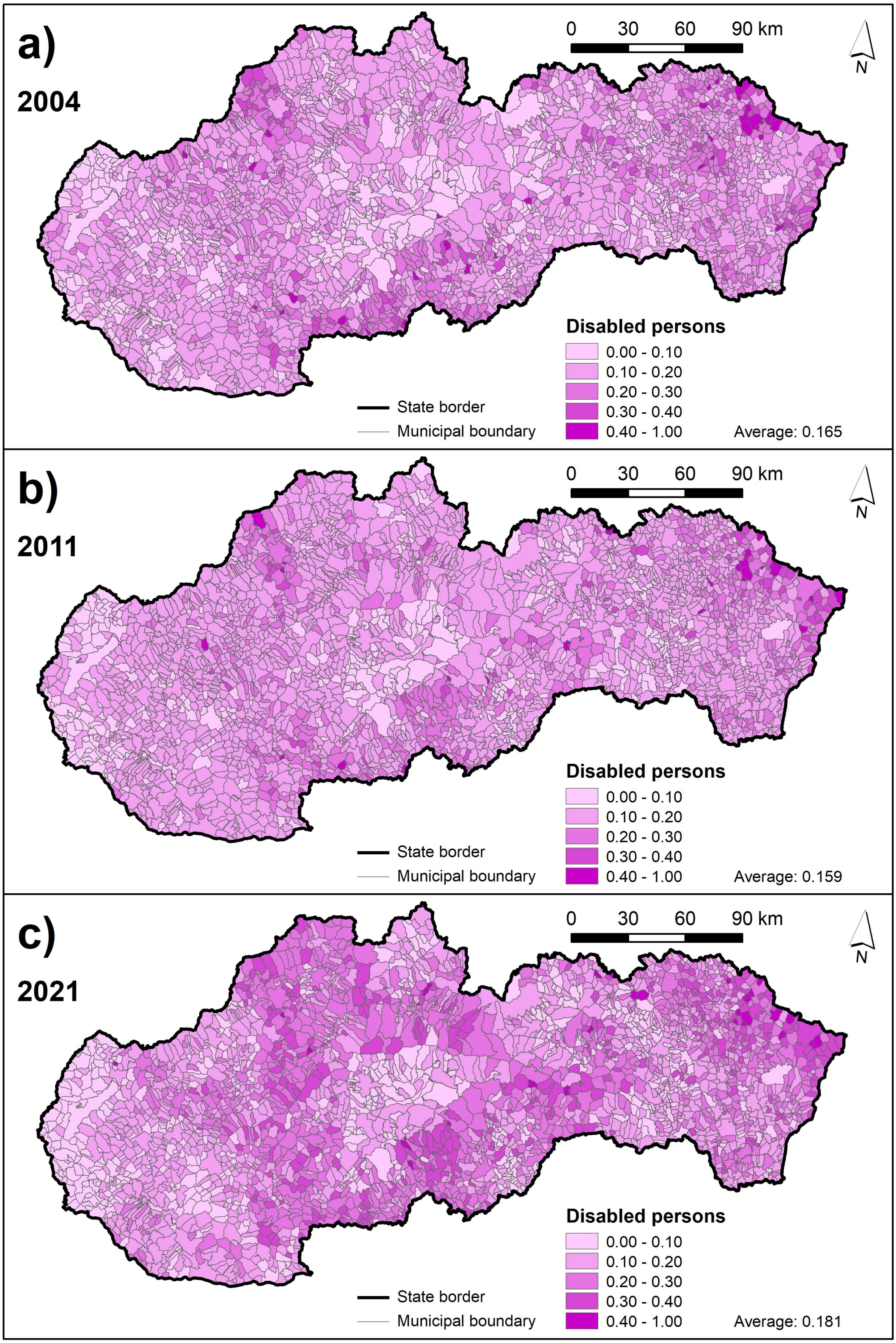

Figure 8. Normalized values of disable population in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

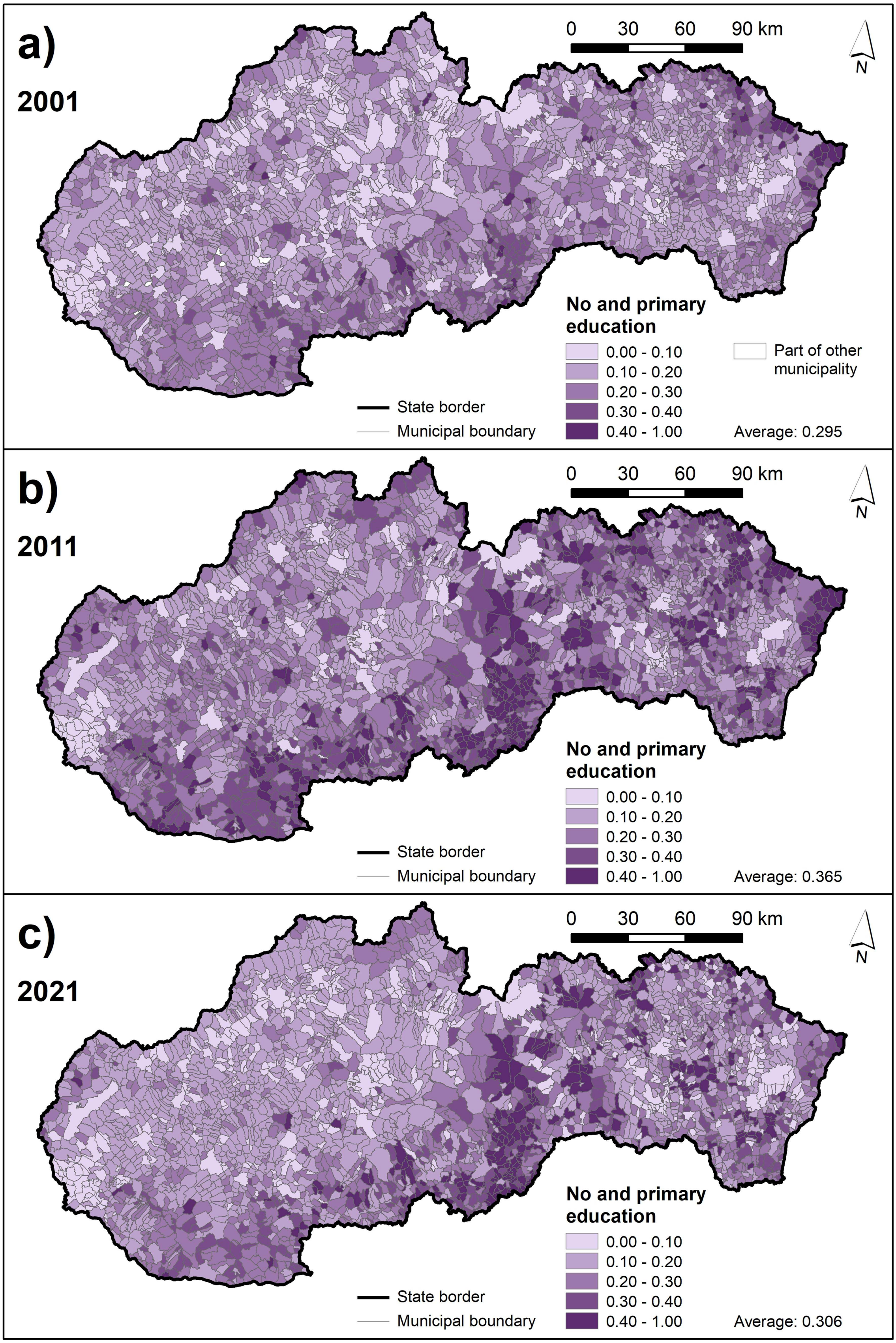

Figure 9. Normalized values of population without/with primary education in municipalities for years: (a) 2001, (b) 2011, and (c) 2021.

4.2 Multicolinearity

The results of the multicollinearity tests are presented in Table 1. The highest VIF value is 2.92 for the indicator of the population without/with primary education. On the other hand, the lowest VIF value of 1.04 was recorded for the indicator of population density. Each indicator had a VIF value of less than 5. Therefore, all the indicators were used as independent indicators to calculate the respective social flood vulnerability indices.

4.3 PCA and factor analysis – interdependencies among indicators

Table 2 presents the Pearson correlation matrices among the indicators and for each of the studied years. A correlation coefficient of 0.7 was used as a minimum threshold to indicate a strong or very strong relationship between indicators (Dorman et al. 2013; Roldán-Valcarce et al. 2023). For all of the indicators, we recorded a correlation value lower than 0.7; therefore, none of them had to be replaced or discarded to avoid double counting.

Using the PCA, it was first necessary for each studied year (2001, 2011, and 2021) to calculate the eigenvalues of the correlation matrix and the percentage of the total variance explained by each principal component (Table 3). This was done in order to determine, in the next step of the analysis (factor analysis), how many factors should be selected in the given dataset so that all eight studied indicators are adequately represented. Table 3 and Figure 10 present the PCA results for the individual years studied. Figure 10 shows the influence of each indicator on the principal component. Moreover, when two vectors are close and form a small angle, the two indicators they represent are positively correlated. However, when they diverge and form large angles, they are negatively correlated. The eigenvalues and percentage of variance explained by the main principal components (PC1–PC8) are listed in Table 3. The first three eigenvalues (principal components PC1, PC, and PC3) explain up to 65.196%, 65.778%, and 69.802% of the total variability of indicators for the years 2001, 2011, and 2021, respectively. Therefore, displaying the scales in a factor plane with three factors is sufficient (Figure 11).

Based on the estimation of the rotated factor loading matrix (values higher than 0.5), presented in Figure 11a, we can see that Factor 1 positively correlates with indicators of the population aged 65+, the population without/with primary education, and the disabled population, whereas it is negatively correlated with the indicator of households with 6+ persons. Factor 1 is thus positively saturated by three indicators. These three indicators can be characterized by one latent variable and that is Factor 1. Similarly, Factor 2 positively correlates with the indicators of the unemployed population, Roma ethnicity, and incomplete households, whereas Factor 3 is negatively correlated with the population density indicator. Figure 11b shows the rotated factor loading matrix for the year 2011. Values higher than 0.5 indicate that Factor 1 is positively correlated with the indicators of the unemployed population, Roma ethnicity, population without/with primary education, and households with 6+ persons. Factor 2 positively correlates with the indicators of the population aged 65+ and the disabled population, while factor 3 negatively correlates with the indicators of incomplete households and population density. Figure 11c depicts the rotated factor loading matrix for the year 2021. Values higher than 0.5 indicate that Factor 1 is positively correlated with five indicators: unemployed population, Roma ethnicity, population without/with primary education, incomplete households, and households with 6+ persons. Factor 2 is positively correlated with indicators of the population aged 65+ and the disabled population, while Factor 3 is positively correlated with the population density indicator.

Table 1. Result of multicollinearity tests among indicators.

Indicator	VIF 2001	VIF 2011	VIF 2021
Population aged 65+	2.37	2.02	1.90
Unemployed population	2.05	2.15	2.81
Roma ethnicity	1.41	1.48	1.37
Population without/with primary education	2.75	2.22	2.92
Incomplete households	1.13	1.10	1.68
Disabled population	1.32	1.49	1.33
Population density	1.07	1.06	1.04
Households with 6+ persons	1.27	1.45	1.54

Table 2. Correlation matrices for each of the studied year.

2001	1	2	3	4	5	6	7	8
1	1							
2	0.04	1						
3	−0.19	0.46	1					
4	0.55	0.58	0.23	1				
5	−0.20	0.19	0.23	0.04	1			
6	0.47	0.11	−0.04	0.34	−0.17	1		
7	−0.15	−0.07	0.02	−0.21	0.07	−0.11	1	
8	−0.36	0.21	0.27	−0.01	0.13	−0.08	−0.08	1
2011	1	2	3	4	5	6	7	8
1	1							
2	−0.17	1						
3	−0.30	0.48	1					
4	0.16	0.65	0.36	1				
5	−0.04	−0.09	0.00	−0.05	1			
6	0.55	0.04	−0.12	0.23	−0.03	1		
7	−0.11	−0.09	0.05	−0.17	0.10	−0.12	1	
8	−0.36	0.31	0.34	0.26	−0.23	−0.09	−0.06	1
2021	1	2	3	4	5	6	7	8
1	1							
2	−0.39	1						
3	−0.31	0.48	1					
4	−0.36	0.67	0.45	1				
5	−0.35	0.55	0.33	0.61	1			
6	0.45	−0.02	−0.09	−0.01	−0.08	1		
7	−0.04	−0.04	0.05	−0.10	0.01	−0.11	1	
8	−0.50	0.45	0.28	0.42	0.28	−0.08	−0.09	1

Note: 1: population aged 65+; 2: unemployed population; 3: Roma ethnicity; 4: population without/with primary education; 5: incomplete households; 6: disabled population; 7: population density; and 8: households with 6+ persons.

Table 3. Results of PCA analysis for studied years.

Principal component	Eigenvalue	2001 % Total variance	Cumulative eigenvalue	Cumulative %
PC1	**2.211**	27.642	2.211	27.642
PC2	**1.973**	24.667	4.185	52.309
PC3	**1.031**	12.887	5.216	**65.196**
PC4	0.843	10.531	6.058	75.727
PC5	0.716	8.949	6.774	84.676
PC6	0.585	7.315	7.359	91.991
PC7	0.440	5.502	7.799	97.493
PC8	0.201	2.507	8.000	100.000
2011				
PC1	**2.335**	29.185	2.335	29.185
PC2	**1.807**	22.589	4.142	51.773
PC3	**1.120**	14.005	5.262	**65.778**
PC4	0.893	11.168	6.156	76.946
PC5	0.652	8.150	6.808	85.096
PC6	0.529	6.617	7.337	91.713
PC7	0.425	5.309	7.762	97.022
PC8	0.238	2.978	8.000	100.000
2021				
PC1	**3.261**	40.756	3.261	40.756
PC2	**1.321**	16.507	4.581	57.264
PC3	**1.003**	12.538	5.584	**69.802**
PC4	0.733	9.165	6.317	78.967
PC5	0.681	8.518	6.999	87.485
PC6	0.428	5.344	7.426	92.829
PC7	0.353	4.413	7.779	97.242
PC8	0.221	2.758	8.000	100.000

Note: The first three eigenvalues (PC1, PC, and PC3) highlighted with bold explain up to 65.196%, 65.778%, and 69.802% of the total variability of indicators for the respective years 2001, 2011, and 2021.

In summary, the PCA was used to redistribute the variance in the correlation matrix using the method of eigenvalue decomposition to individual principal components. The rotated component matrix represents the component matrix of three principal components after varimax rotation with Kaiser normalization applied for eight selected indicators. These three principal components (i.e. Factors 1, 2, and 3) explain the variance in the respective dataset, which recorded similar values in the case of each studied year.

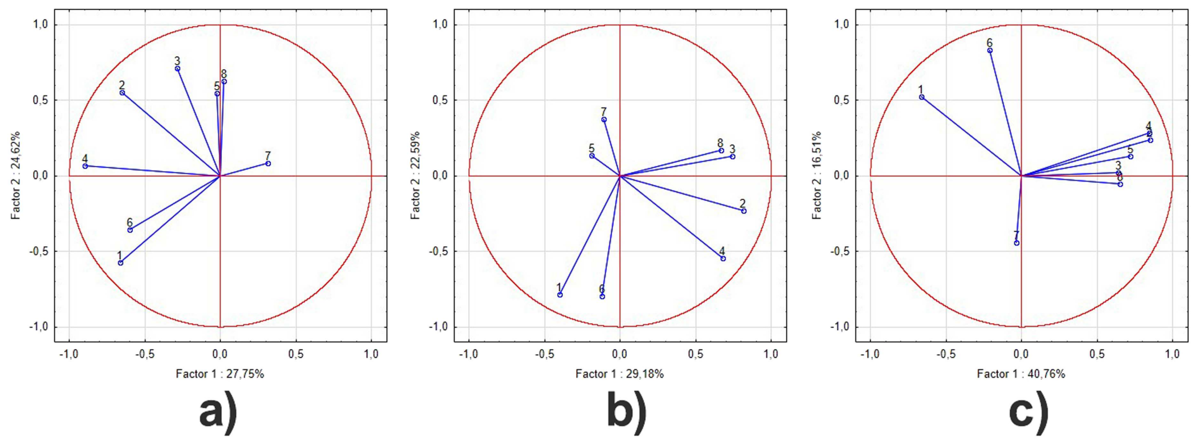

Figure 10. PCA loadings plot of the principal components: (a) 2001, (b) 2011, and (c) 2021. Note: 1 – population aged 65+; 2 – unemployed population; 3 – Roma ethnicity; 4 – population without/with primary education; 5 – incomplete households; 6 – disabled population; 7 – population density; 8 – households with 6+ persons.

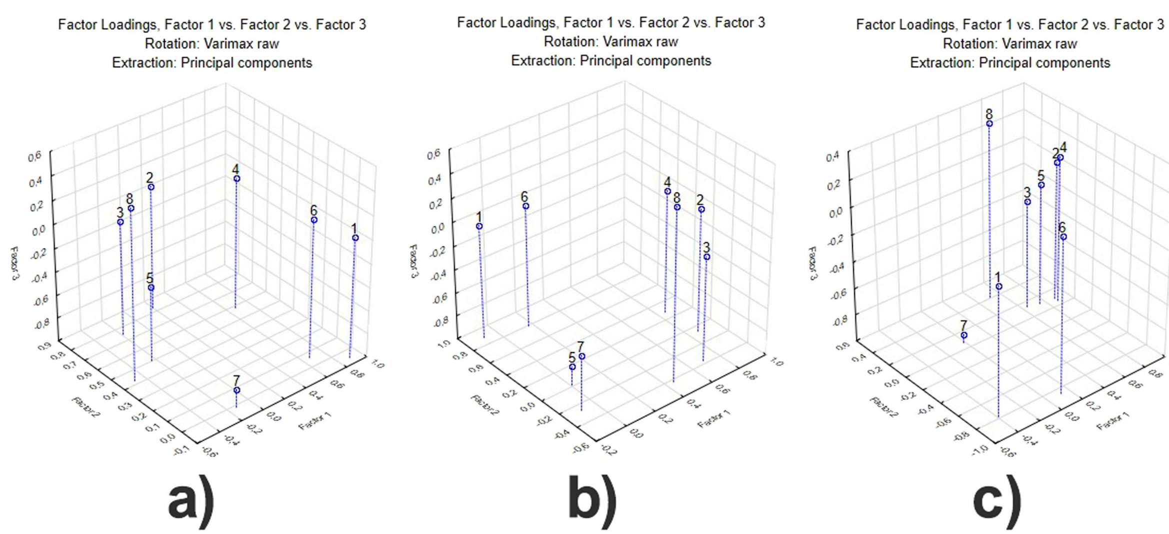

Figure 11. Indicators shown on the factor plane with three factors: (a) 2001, (b) 2011, and (c) 2021. Note: 1 – population aged 65+; 2 – unemployed population; 3 – Roma ethnicity; 4 – population without/with primary education; 5 – incomplete households; 6 – disabled population; 7 – population density; 8 – households with 6+ persons.

4.4 Variance analysis of indicators

Figure 12 shows the distribution of the arithmetic mean values and standard deviations, which form the basis for the one-factor analysis of variance.

Figure 13 points out the changes in individual vulnerability indicators throughout the studied years. Since the calculated probability p-value for all indicators, except the population density, is less than 0.01, we reject the null hypothesis at the significance level $\alpha = 0.01$. This means that the differences between the arithmetic means of these indicators in the years 2001, 2011, and 2021 are statistically significant. In other words, variance analysis confirmed that the arithmetic means of these seven indicators in the individual studied years 2001, 2011, and 2021 are statistically significantly different. Basically, we can say the same also in the case of the population density indicator. However, the p-value is less than 0.05, so we reject the null hypothesis at the significance level $\alpha = 0.05$.

The results of Scheffe's test provided information on which years were different with respect to the arithmetic mean value of the indicator. Based on Table 4, we see that the p-values are less than 0.01 in

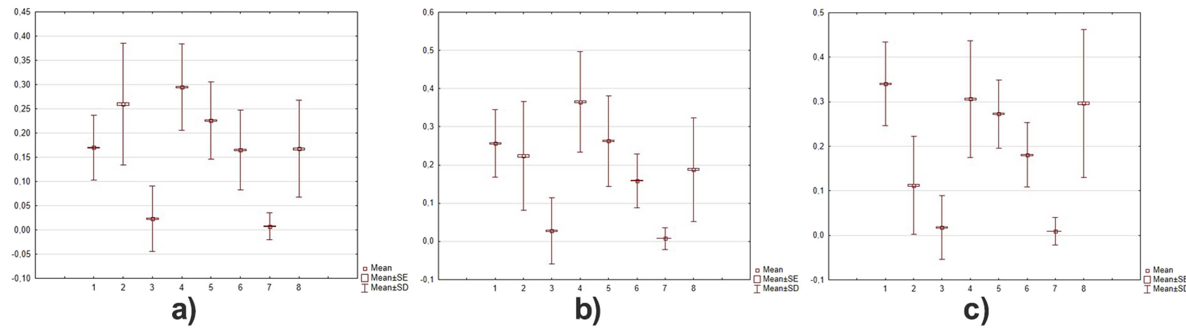

Figure 12. Arithmetic mean values and standard deviations of indicators in the studied years: (a) 2001, (b) 2011, and (c) 2021. Horizontal axis: 1 – population aged 65+; 2 – unemployed population; 3 – Roma ethnicity; 4 – population without/with primary education; 5 – incomplete households; 6 – disabled population; 7 – population density; 8 – households with 6+ persons.

almost all the cases, which means that there are statistically significant differences (at the significance level of $\alpha = 0.01$) in the arithmetic mean values of these indicators between individual years. However, the p-value is higher than 0.01 or 0.05 in case of the Roma ethnicity for 2001 and 2011 (not statistically significant) and for 2001 and 2021 (statistically significant at the significance level of $\alpha = 0.05$). This is also the case for the disabled population in 2001 and 2011, which are statistically significantly different at a significance level of $\alpha = 0.05$. In the case of population density, the arithmetic mean values of this indicator between individual years were not statistically significant. This means that the changes in population density throughout the years were not as prominent as those in the other indicators used.

4.5 Spatial and temporal changes in the SFVI

Figure 14 presents the resulting SFVI for the individual years studied. Based on the average value, which falls within the middle interval, we can claim that the social vulnerability of municipalities to flooding increased in each of the studied years from 0.164 in 2001, 0.186 in 2011, and 0.192 in 2021. The municipalities with the highest values of SFVI throughout the years can be localized mainly in southern and eastern Slovakia, where the flood potential is also quite significant (mainly eastern Slovakia), as reported by Vojtek (2023). Table 5 shows the distribution of municipalities in the SFVI classes each year. The number of municipalities in the first and second classes gradually decreased from 2001, 2011 to 2021 while the number of municipalities in the middle, fourth, and fifth classes increased throughout the studied years. Overall, we can claim that the social vulnerability of municipalities to floods has increased, and more municipalities have become vulnerable to flooding.

Figure 15 shows the changes in the SFVI throughout the study period. Because the calculated probability p-value = 0.000 for the SFVI is less than 0.01, we reject the null hypothesis at the significance level $\alpha = 0.01$. This means that the differences between the arithmetic means of the SFVI in 2001, 2011, and 2021 were statistically significant. The result of the Scheffe's test (p-value = 0.000) for the SFVI is less than 0.01 in all the studied years, which means that the arithmetic mean value of the SFVI is statistically significantly different from the arithmetic mean values in 2011 and 2021.

4.6 Correlation between the SFVI and flood frequency

As can be seen in Figure 16, the overall and average number of flood events in the municipalities of Slovakia were very similar for the periods 1992–2001 and 2012–2021, with average values of 0.543 and 0.531, respectively. However, their spatial patterns were quite different. In the 1992–2001 period, floods were most frequent in eastern and northern Slovakia, while in the period 2012–2021, the situation also included central Slovakia, with the exception of eastern and northern Slovakia. The highest number of flood events occurred in the period 2002–2011, where fluvial and pluvial floods from 2010 were the most prominent, affecting the highest number of municipalities. Based on the Reports on the Course and

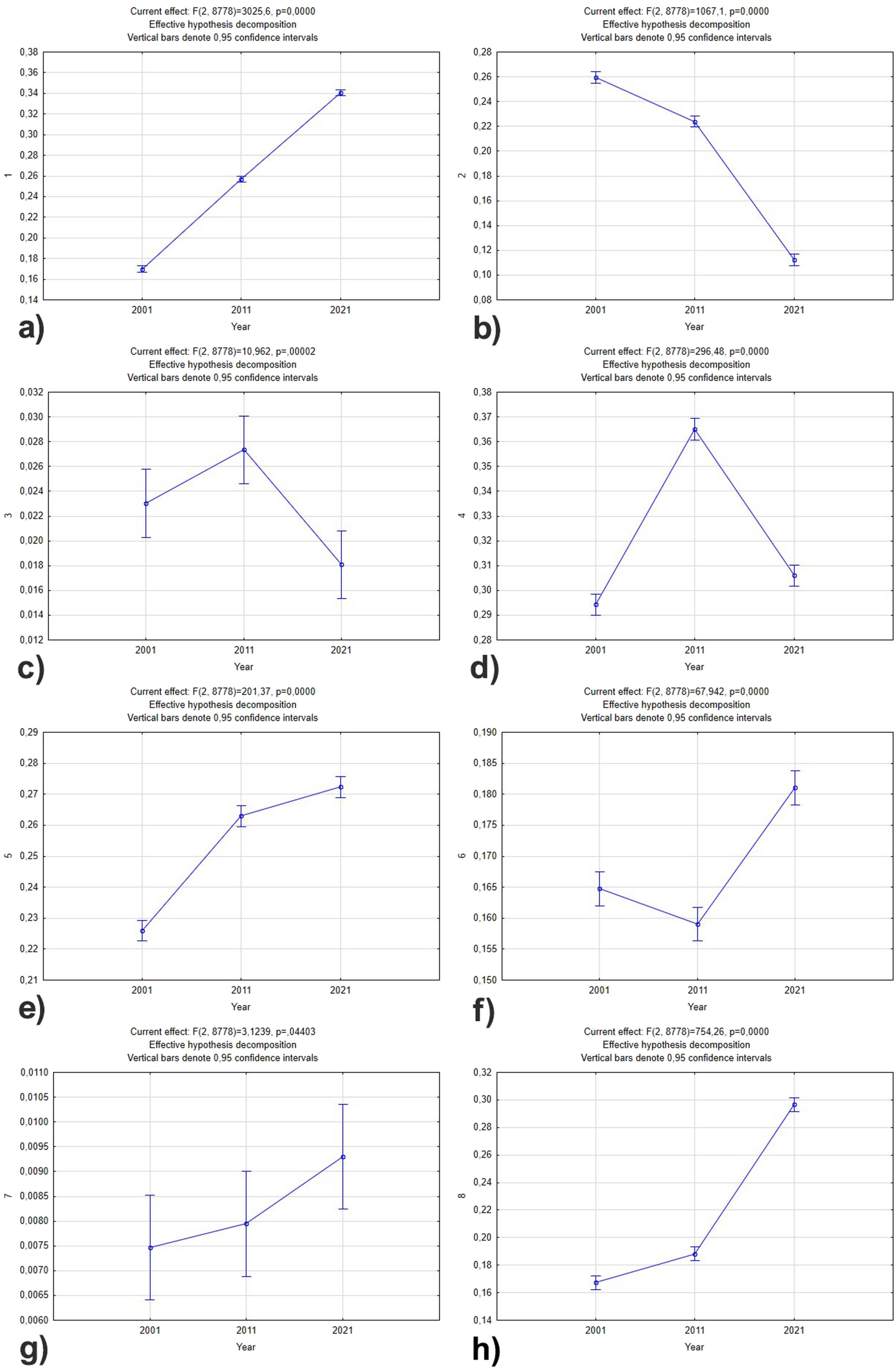

Figure 13. Changes in vulnerability indicators throughout the studied years: (a) population aged 65+, (b) unemployed population, (c) Roma ethnicity, (d) population without/with primary education, (e) incomplete households, (f) disabled population, (g) population density, (h) households with 6+ persons.

Table 4. Results of the Scheffe's test (p-values).

1	2011	2021	2	2011	2021	3	2011	2021	4	2011	2021
2001	0.000	0.000	2001	0.000	0.000	2001	0.095	0.043	2001	0.000	0.001
2011		0.000	2011		0.000	2011		0.000	2011		0.000
5	2011	2021	**6**	2011	2021	**7**	2011	2021	**8**	2011	2021
2001	0.000	0.000	2001	0.014	0.000	2001	0.819	0.055	2001	0.000	0.000
2011		0.001	2011		0.000	2011		0.206	2011		0.000

Note: 1: population aged 65+; 2: unemployed population; 3: Roma ethnicity; 4: population without/with primary education; 5: incomplete households; 6: disabled population; 7: population density; and 8: households with 6+ persons.

Consequences of Floods in the Slovak Republic, a total of 850.6 mil. Euros were spent for rescue/recovery costs and overall damage to assets in the period 2002–2011. However, only floods from 2010 caused rescue/recovery costs (53.9 mil. Euros) and damage to assets (480.8 mil. Euros) resulted in a total of 534.7 mil. Euros. In 2010, Slovakia recorded an annual precipitation total of 1255 mm, representing 165% of the long-term average. In western, central, and eastern Slovakia, the increase in annual precipitation represented 157, 162, and 171% of the long-term average, respectively. Exceptionally above-normal precipitation totals were recorded in May and July. In May, the total precipitation across Slovakia reached 235 mm, which represents 309% of the long-term monthly average. The second rainiest month was July, with a nationwide total of 153 mm, representing 170% of the long-term monthly average. All of these rainfall conditions resulted in significant flood events in 2010 that occurred mostly in May and July in almost all parts of the country (SHMI, 2010).

The correlation between the individual periods of flood events and the SFVI resulted in positive correlation values, although the strength of the correlation was low. The Pearson correlations between the SFVI 2001 and the number of flood events in the period 1992–2001, 2002–2011, and 2012–2021 were 0.01, 0.07, and 0.02, respectively.

4.7 Spatial clusters of indicators and SFVI

The results of spatial autocorrelation in the cases of individual indicators and SFVI were statistically significant and clustered, as shown in Table 6 and supplementary Figures S1–S12. Table 6 presents the calculated local Moran's coefficients, z-scores, and p-values for respective indicators and SFVI in each studied year. The local Moran's coefficients resulted in the following values within the studied years: population aged 65+ (≈0.3), unemployed population (≈0.5), Roma ethnicity (≈0.2), population without/with primary education (≈0.4), incomplete households (≈0.2), disabled population (≈0.4), population density (≈0.3), and households with 6+ persons (≈0.5). The local Moran's coefficients for the SFVI recorded the values of 0.42 (2001), 0.43 (2011), and 0.46 (2021).

Figure S1 presents the indicator of the population aged 65+, where the spatial pattern of hot and cold spots is very similar each year. The number of municipalities with high–high (HH) spatial dependence decreases over time while the number of municipalities with low–low (LL) spatial dependence increases. Spatial outliers, i.e. high–low (HL) and low–high (LH) spatial dependence, slightly increase in both cases. Figure S2 shows that the indicator of the unemployed population has a similar spatial pattern in 2001 and 2011, with similar numbers of municipalities with HH, LL, HL, and LH spatial dependence. In 2021, the numbers of municipalities with HH, LL, HL, and LH spatial dependence decreased, and specifically, we can see different patterns and significant decreases in LL clusters. Figure S3 shows a similar spatial pattern of hot and cold spots in the case of the Roma ethnicity indicator; however, there is a decreasing number of municipalities with HH spatial dependence and zero municipalities with LL spatial dependence each year. The spatial pattern of the population without/with primary education is shown in Figure S4. The number of municipalities with HH spatial dependence increased from 2001 to 2011, but then decreased in 2021. The number of municipalities with LL spatial dependence decreases throughout the studied years, with a significant decrease in 2021. Figure S5 presents quite different spatial patterns of incomplete households in each of the studied years, with a gradual increase in the number of municipalities with HH spatial dependence. The number of municipalities with LL spatial dependence increased from 2001 to 2011 and decreased in 2021. Figure S6 shows very similar spatial pattern for the disabled population each year. The number of municipalities with HH spatial dependence decreased from 2001 to 2011 and increased in 2021.

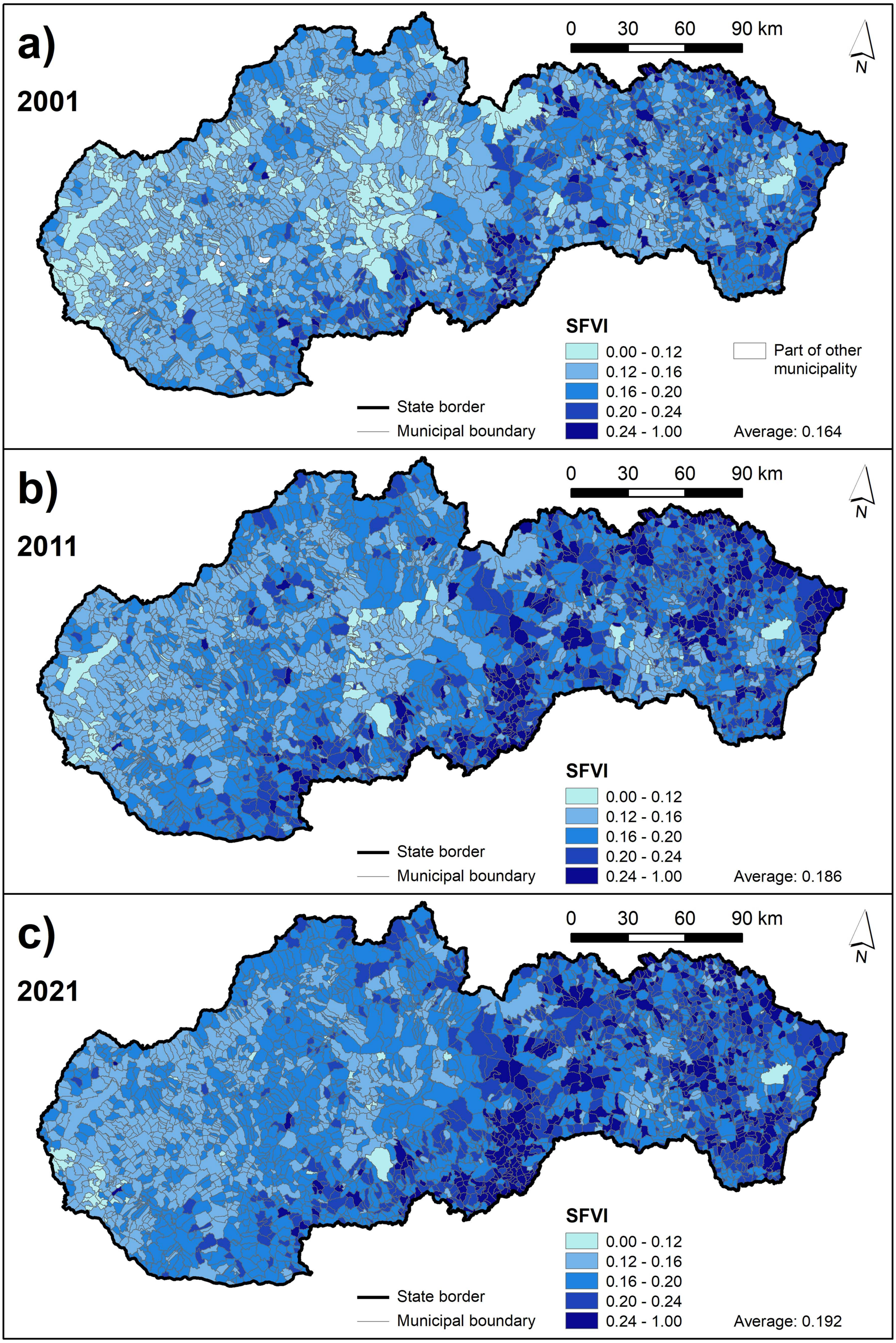

Figure 14. SFVI in municipalities of Slovakia for the year: (a) 2001, (b) 2011, and (c) 2021.

Table 5. Number of municipalities in SFVI classes for the years 2001, 2011, and 2021.

SFVI class	2001	2011	2021
0.00–0.12	233	67	38
0.12–0.16	1332	845	663
0.16–0.20	907	1160	1277
0.20–0.24	308	507	587
0.24–1.00	139	348	362

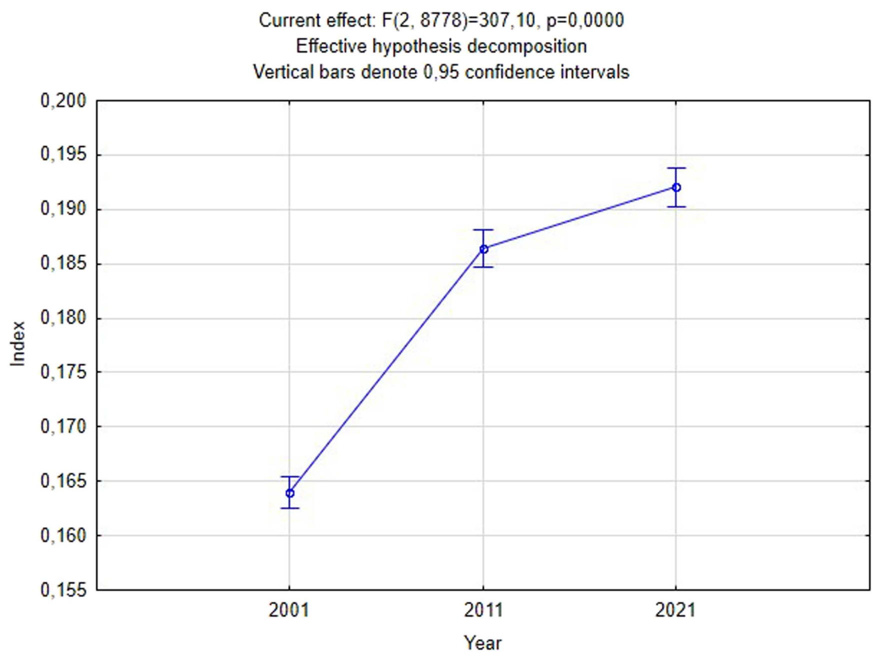

Figure 15. Statistically significant changes in the SFVI throughout the studied years.

The number of municipalities with LL spatial dependence gradually increased from 2001 to 2021. Figure S7 presents basically the same spatial pattern of population density, with a slight increase in the number of municipalities with HH spatial dependence, mainly around major cities in Slovakia. Figure S8 shows a similar spatial pattern in the case of households with 6+ persons. However, a decrease in the number of municipalities with HH and LL spatial dependence was observed in 2011 compared to 2001 and 2021.

Figure S9 shows the results of spatial autocorrelation for SFVI. In 2001, 258 and 237 municipalities had HH and LL spatial dependence, respectively. Compared to 2001, the number of municipalities with HH and LL spatial dependence in 2011 was higher by 0.3%. In 2021, the number of municipalities with HH and LL spatial dependence decreased to 249 municipalities and 187 municipalities, respectively. Furthermore, the Moran's scatter plots for individual indicators and the final SFVI are presented in supplementary Figures S10–S12.

5 Discussion

Social vulnerability to flooding is an important task in flood risk studies, as different groups of population do not have the same conditions to resist, recover or cope with floods (Cutter et al. 2003). In this study, we analyzed spatial and temporal changes in social flood vulnerability, which are important for understanding the trajectories of its possible development in the future as well as to adopt flood preparedness or protection measures. We used specific vulnerability indicators for determining the SFVI in 2001, 2011, and 2021using the indicator-based approach, and we analyzed its spatial and temporal changes by applying various spatial and statistical methods. Besides this study, the effective use of PCA and factor analysis in

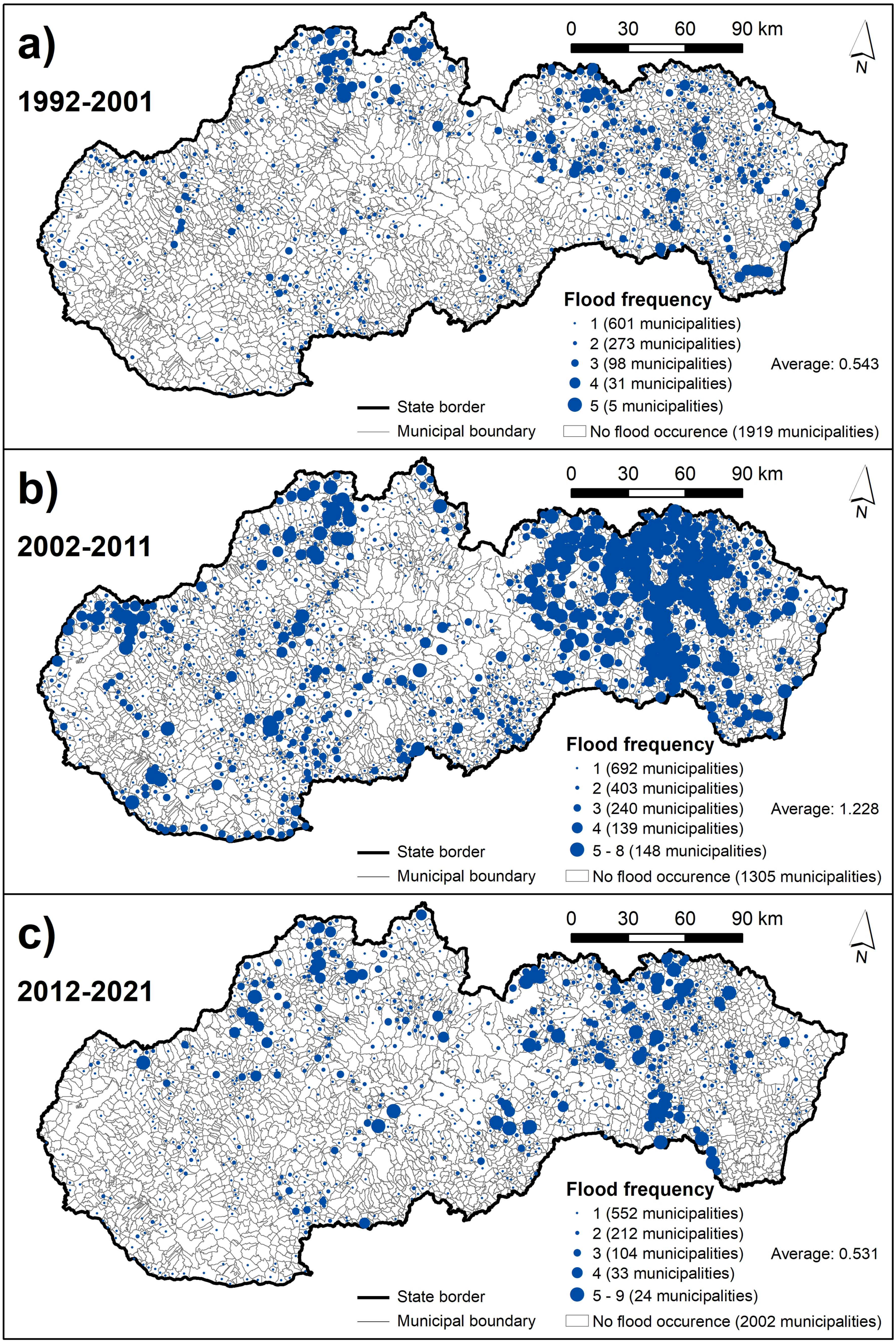

Figure 16. Number of flood events in municipalities of Slovakia in the periods: (a) 1992–2001, (b) 2002–2011, and (c) 2012–2021.

Table 6. Results of spatial autocorrelation analysis for individual indicators and SFVI for 2001, 2011, and 2021.

Indicator/index	Statistics	2001	2011	2021
Population aged 65+	local Moran's coefficient	0.274	0.262	0.250
	z-score	25.351	24.174	23.102
	p-value	0.000	0.000	0.000
Roma ethnicity	local Moran's coefficient	0.149	0.154	0.120
	z-score	13.889	14.309	11.258
	p-value	0.000	0.000	0.000
Population without/with primary education	local Moran's coefficient	0.442	0.441	0.417
	z-score	40.699	40.591	38.472
	p-value	0.000	0.000	0.000
Incomplete households	local Moran's coefficient	0.129	0.163	0.186
	z-score	11.934	15.078	17.166
	p-value	0.000	0.000	0.000
Disabled population	local Moran's coefficient	0.365	0.348	0.349
	z-score	33.649	32.179	32.303
	p-value	0.000	0.000	0.000
Population density	local Moran's coefficient	0.280	0.287	0.329
	z-score	29.191	29.536	33.048
	p-value	0.000	0.000	0.000
Households with 6+ persons	local Moran's coefficient	0.546	0.485	0.502
	z-score	50.312	44.713	46.223
	p-value	0.000	0.000	0.000
SFVI	local Moran's coefficient	0.416	0.432	0.459
	z-score	38.316	39.807	42.284
	p-value	0.000	0.000	0.000

vulnerability studies has been confirmed by several recent studies, such as Bucherie et al. (2022), Abdrabo et al. (2023), Arunachalam et al. (2023) or Roldán-Valcarce et al. (2023). The spatial autocorrelation used in this study supplemented the other spatial-statistical methods to obtain a comprehensive picture of social flood vulnerability development over time at the municipal level in Slovakia. In addition, it has to be noted that studies focused on spatial and temporal changes in (social) vulnerability to floods at the municipal level are rare in the literature, and no such studies exist, specifically for the territory of Slovakia.

Our study builds on the social vulnerability index (SoVI) methodology and methodical aspects of temporal and spatial changes in social vulnerability to natural hazards, which were introduced by Cutter and Finch (2008). In this study, we similarly used PCA and factor analysis as well as the spatial autocorrelation (local Moran's coefficient) to analyze spatial clusters of SFVI. With respect to the work of Cutter and Finch (2008), one of the differences is in the number and type of indicators used. Furthermore, we complemented the assessment of changes in SFVI over the time by applying the method of variance analysis. Using this method, we verified whether the differences in arithmetic means of indicators and the SFVI were statistically significant. When comparing the differences between individual years in the variance analysis, we also used Scheffe's post hoc test.

Following the results achieved, we found out that the social vulnerability of municipalities to flooding had an increasing trend. This was confirmed by the average values of SFVI in each studied year, which increased from 0.164 in 2001 to 0.186 in 2011 and 0.192 in 2021 (Figures 14 and 15). The municipalities with the highest values of SFVI throughout the years can be localized mainly in southern and eastern Slovakia, as shown in Figure 14. This finding was also confirmed by spatial autocorrelation analysis. Figure S9 shows that municipalities with HH (hot spots) spatially dependent on the SFVI are located exactly in southern and eastern Slovakia. The increase in the social vulnerability of municipalities to floods over time is significantly influenced by the spatial and temporal development of individual indicators. As presented in Figure 13, four indicators (population aged 65+, incomplete households, population density, and households with 6+ persons) have an overall increasing trend throughout the studied years while one indicator (disabled population) recorded a slight decrease from 2001 to 2011, but an increase in 2021. Moreover, one indicator (unemployed population) recorded an overall decreasing trend, and two indicators (Roma ethnicity and population without/with primary education) recorded an increase from 2001 to 2011, but a decrease in 2021.

We can identify several insights from the spatial analysis of indicators throughout the studied years. In the case of the population aged 65+, Figure 3 shows a continuous increase in the population of this age category from 2001 to 2021, meaning that the population aged across whole Slovakia. The increasing trend of the share of elderly residents in municipalities of Slovakia means higher flood vulnerability towards the future, as the elderly population is less resilient to flood situations and has more difficulties to recover from floods. Similar finding was achieved by Yang et al. (2025), who confirmed that population aging exacerbates flood risk to the elderly in European regions. Moreover, a study by Aggarwal et al. (2025) confirmed that exposure to severe flood events was associated with increased hospitalization rates for skin diseases, nervous system diseases, musculoskeletal system diseases, and injuries among the population aged 65+.

The development of the unemployed population clearly shows a decreasing trend across whole Slovakia (Figure 4). Higher shares of the unemployed population are in southern-central and eastern Slovakia, which is also associated, to a considerable extent, with a greater presence of the Roma ethnicity. An overall decreasing trend of unemployment means higher opportunities for recovering from floods across Slovakia's municipalities. However, for southern-central and eastern Slovakia, the situation remains relatively stable over the studied period, with a high number of HH clusters (Figure S2). As stated by Solín (2012), a lack of financial resources in municipalities with high unemployment rate is also the reason why people do not insure their property for flood situations, which makes them more vulnerable.

The presence of Roma ethnicity significantly correlates with unemployment in municipalities, as confirmed by the Pearson correlation values presented in Table 2. The highest shares of Roma ethnicity are in southern-central and eastern Slovakia and remain relatively stable throughout the studied years (Figure 5). In these regions, Roma communities often live in marginalized areas and in proximity of rivers with inadequate infrastructure due to poverty and social exclusion. This makes them highly vulnerable to flood hazard, which damages homes, contaminates water, and causes displacement, exacerbating existing health and economic disparities. Studies from Slovakia by Solín (2012, 2025) are in line with our results. The author confirmed that Roma settlements experience higher flood risks and impacts compared to the general population. Moreover, a study from Romania by Alexandrescu et al. (2021) confirmed that Roma's higher exposure, sensitivity, and reduced adaptive capacity increase their vulnerability to future extreme flood events, thus lowering their adaptation to floods.

The indicator of households with 6+ persons is significantly correlated with unemployment, Roma ethnicity, and population without/with primary education, as shown in Table 2. The highest shares of these households are in municipalities located in eastern, but also northern Slovakia. This is also caused by higher natality in these regions compared to other regions of Slovakia. The increasing trend of this indicator throughout the studied years is shown in Figure 6,while Figure S8 shows a relatively stable spatial pattern of LL or HH clusters. This means that in the future, Slovakia's municipalities could expect higher numbers of households with 6+ persons, especially in eastern and northern Slovakia. This will result in higher vulnerability due to lower possibilities to resist or recovering from floods, especially in the case of households with more elderly, children, or disabled members. This is in line with the study by Tu et al. (2024), who also pointed out that there is some degree of pre-existing adaptation problems in households before the actual flood situation occurs.

Incomplete households recorded relatively different spatial patterns throughout the studied years but an increasing number of HH clusters (Figure S5). Moreover, an increasing trend across municipalities in Slovakia and the studied years can also be seen in Figure 7. For future social flood vulnerability situation in Slovakia, it means that more households (often single-parent or female-headed) will have problems to buy an insurance or recover from floods. This assumption is also supported by the high Pearson correlation with the unemployed population indicator in 2021. Similar finding was achieved by Osberghaus (2021) who found out, via the survey of 8000 households in Germany, that low-income and incomplete households, owing to their smaller homes and less valuable assets, face higher expected flood damage.

The spatial pattern of municipalities with either LL or HH values of disabled population is relatively the same throughout the studied years, as shown in Figure S6. These indicators are significantly correlated with the population aged 65+ based on Table 2. Similarly as population aged 65+, the development of the disabled population from 2001 to 2021 shows an increasing trend across municipalities of Slovakia (Figure 8). Based on this result, we can assume that this trend will continue and it will mean to Slovakia's municipalities that there will be more barriers for disabled to accessing disaster risk information and warnings, difficulties in understanding emergencies, challenges in communicating needs, or evacuation and mobility problems, as reported by Nguyen-Trung et al. (2025). This is in line with the household survey performed by Morales (2025), who concluded that individuals with vision or multiple disabilities experienced significantly longer periods of displacement compared to non-disabled people. Moreover, people with cognitive disabilities reported significantly higher levels of mental distress than their non-disabled counterparts.

The highest values of Pearson correlation were achieved between the unemployed population and the population without/with primary education throughout all studied years. Moreover, the population without/with primary education also significantly correlates with the Roma ethnicity indicator (Table 2). Therefore, similar spatial patterns of HH clusters can be seen in Figures S2, S3, and S4. Based on the decrease in the share of the population without/with primary education from 2011 to 2021 (Figure 9), we expect further decreases in the future. In general, this could mean that literacy about flood hazard and flood preparedness will increase among Slovakia's population. This is in line with the findings of the study by Gülsoy et al. (2025), who found out that lower education levels, decreased income, and increased average age were associated with reduced disaster literacy and disaster preparedness levels. In the case of population density, it has an increasing trend, specifically in larger cities (Casali et al. 2024), as shown in Figure 2. Highly dense urban areas are expected to be more vulnerable than less dense rural areas with smaller population. This is in line with other works, such as Zhang et al. (2025).

In summary, our results reveal diverse spatial patterns in indicator development. The development of these indicators over time, as well as their equal weighting, had the greatest influence on the resulting increasing trend in SFVI. The main finding of this study is that more municipalities have become vulnerable to flooding throughout the studied years, and this trend is anticipated for future development of social flood vulnerability in municipalities of Slovakia.

Potential limitations of this study may arise from the data or specific methods used. For the data, we relied on statistical data from statistical databases and censuses, which are processed by the Statistical Office of the Slovak Republic. Although they are considered to be without errors or missing data, the collection of such data, especially from censuses, heavily relies on the answers of inhabitants to the questionnaire survey. The census survey is compulsory, but on the other hand, it can potentially create space for unintentional mistakes or intentionally false answers. Regarding the choice of indicators, we are aware that the literature provides several other indicators that might potentially be used. However, in our case, there were problems with either data availability or their consistence across the statistical databases. As a result, we chose readily available indicators, which characterize vulnerable groups of population from different spectra of social systems, possibly having problems to resist, recover or cope with flooding.

Moreover, the equal weighting of indicators ensured that all of them were equally important for the calculation of the SVFI in each studied year. Equal weighting was chosen to maintain the same objective method for weighting (i.e. same weights) throughout the studied years, which would not be influenced by subjective or different weighting of one indicator over another (Cutter and Finch 2008; Wehbe and Baroud 2024). Wu (2021) stated that if the weights of indicators are taken from the PCA, such weights may not necessarily reflect the actual importance of a specific indicator toward flood vulnerability, and the effect direction of the indicators may vary. Therefore, we chose the equal weighting approach, which is common in the literature, as exemplified by other flood vulnerability studies, such as Nazeer and Bork (2021); El-Zein et al. (2021) or Hinojos et al. (2023).

6 Conclusion

In this study, we focused on place-based, indicator-based, and spatial-statistical approaches for mapping and assessing spatio-temporal changes in social flood vulnerability at the municipal level in Slovakia. Based on eight vulnerability indicators that were analyzed spatially and statistically, we computed the resulting SFVI for each year. The highest SFVI values were found in the southern and eastern parts of Slovakia. The results indicate that the social vulnerability of municipalities to floods has an increasing trend, and more municipalities became vulnerable to flooding in 2001, 2011, and 2021. The changes in the SFVI between the studied years were statistically significant, and this also applies to almost all the indicators, except the population density, for which no statistical significance was found between the studied years.

Recommendations that arise from this study are concerned mainly with the applied methodology for mapping and assessing the spatial and temporal changes in social flood vulnerability, which is comprehensive and sufficiently detailed using readily available data. Our approach contributes to the development of a systematic assessment of social flood vulnerability at the municipal level in Slovakia, taking into account spatial and temporal scales.

The results of this study are practically important for integrated flood risk management on a national scale. The prioritization of municipalities with higher SFVI values in terms of flood measures and strategies should be prioritized. It is also important for municipalities as such, which could take more responsibility in decentralized flood risk management by addressing various aspects of flood prevention, mitigation, protection or adaptation.

For future research, we intend to focus on assessing the spatio-temporal changes and prediction of not only the vulnerability component but also the hazard and exposure components and their synthesis into the flood risk index, which would be compared within past, present, and future time horizons.

Author contributions

CRediT: **Matej Vojtek:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Writing – original draft, Writing – review & editing; **Anna Tirpáková:** Methodology, Software, Visualization, Writing – original draft; **Gabriela Repaská:** Data curation, Resources, Software; **Jana Vojteková:** Data curation, Software, Visualization, Writing – original draft.

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Data availability statement

Requests for the data used in this study can be sent to the corresponding author.

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