Swedish Civil Contingencies Agency

Research/Study

Evaluation of the Social Vulnerability Index (SVIS) in Sweden

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Summary: Social vulnerability assessments have emerged as a suitable tool to better understand the effects of natural hazards. In contrast, there is a mismatch observable between the growing number of studies on social vulnerability and related assessments and the understanding of their empirical validity. The purpose of this study is to evaluate the Social Vulnerability Index (SVIS) developed by Haas et al. (2022) using a local sensitivity analysis approach.

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1 Introduction

1.1 Background

There is no universal concept of vulnerability and for this reason there is a wide range of definitions in the literature deriving from different scientific disciplines (climate change research, natural and social science, engineering, etc.). Over the past decades, social vulnerability assessments have emerged as a suitable tool to better understand the effects of natural hazards on societies, to quantify and map human characteristics responsible for potential loss, and develop capacities and capabilities to respond to the emerging threats of natural hazards (Wisner, 2004; Tate, 2012; Wood et al., 2021). Research efforts and practical applications, including description of assessment procedures, types of vulnerabilities and methods for their evaluation as well as conceptual backgrounds are available in a variety of textbooks (see e.g., Fuchs & Thaler, 2018). Assessment methods include either qualitative approaches or semi-quantitative, often spatially explicit, place-based approaches, many of them with empirical background in respective case studies around the world (Cutter et al., 2003; Fekete, 2019).

Disaster scholars have described processes that transform social, economic and political marginalization into adverse human impacts, resulting in vulnerabilities (Wisner, 2004; Rufat et al., 2019). Geospatial analysts have translated these adverse human impacts in relationships using different variables to construct indices of social vulnerability to natural hazards (Cutter et al., 2003; Fekete, 2009; Tapsell et al., 2010). Quantification of social vulnerability can help to identify which places are most vulnerable, which parts of the population is most susceptible, and which dimensions of social vulnerability are the key drivers to convert vulnerabilities into resilience (Rufat et al., 2015). The benefits of indexes in reducing complexity and visualising results are reflected in their growing promotion by public authorities and their increasing use by governments focusing on disaster planning, on setting priorities in disaster risk reduction, and in resource allocation for both, short term response and long-term strategic loss reduction (Rufat et al., 2019; Zuzak et al., 2022). Despite these efforts, it is still important to carefully examine the potential benefits and limitations of these assessments, particularly those that focus on mapping and place-based approaches, in order to fully understand their value (Fekete, 2019).

Social scientists and disaster modellers typically use demographic and economic data to build algorithms describing the effect of social, economic, political and institutional parameters on the spatial distribution of individual's susceptibility to natural hazards. However, when it comes to validation, modellers have been stymied in large part because social vulnerability is not a directly observable phenomenon (Schmidtlein et al., 2008; Tate, 2012; Spielman et al., 2020). Consequently, indicator selection and indices validation require the use of proxies and different approaches can be found in the literature (e.g., Gall, 2007; Fekete, 2009; Burton, 2010). Furthermore, a less-well explored approach is the internal validation of social vulnerability indexes (Schmidtlein et al., 2008; Tate, 2012, 2013; Spielman et al., 2020), which is needed to assess the robustness of indexes and to identify how changes in the index construction may lead to changes in social vulnerability.

1.2 Rationale

In general, studies relying on social vulnerability indices are based on the following steps (see e.g. Cutter et al., 2003):

1. All input variables have to be standardised according to z-scores (that is generating variables with a mean of 0 and a standard deviation of 1).
2. A PCA (Principal Component Analysis) with the standardised input variables must be performed. A statistical technique called principal component analysis (PCA) is used to transform observations of potentially associated properties into main components that are unrelated to one another. The initial variables are combined in linear fashion. They aid in gathering as much information as possible for the data set.
3. The number of components to be used has to be selected based on different approaches (e.g. the Kaiser Criterion).
4. To avoid variables having high loading in two different components, the initial PCA result has to be rotated.
5. The resulting components have then to be interpreted on how they may influence (social) vulnerability, and positive or negative signs have to be assigned to the components according to their influence (positive values = increasing vulnerability, negative values = decreasing vulnerability).
6. The selected component scores are further combined into a univariate score using an equal or unequal predetermined weighting scheme.
7. The resulting scores are then standardised to mean 0 and standard deviation 1.
8. Finally, results are displayed and further analysed using maps and tables.

Parameters and decisions that may have a large impact on the outcome include changes in the set of variables used, difference in scale of the analysis and changes in the (subjective) decisions made in the index algorithm (Schmidtlein et al., 2008). By gaining a better understanding of how the index responds to changes, we can more confidently interpret and implement the results. The latter is the realm of sensitivity analysis, which evaluates how changes in input data and parameters can affect the output of the model. This type of analysis is useful for identifying the factors that have a larger impact on the output, and for assessing the robustness of the model facing different underlying uncertainties. By conducting sensitivity analysis, we can gain a better understanding of the factors that drive the output of the model and make more informed decisions about how to use it.

There are several different types of sensitivity analysis, including local where model sensitivity is assessed one index construction stage at a time; and global which allows simultaneous evaluation of multiple construction stages (C. Xu & G. Z. Gertner, 2008). Both approaches provide the modeller with important metrics to assess the importance of different modelling methods and decisions.

The purpose of this study is to systematically evaluate the Social Vulnerability Index (SVIS) developed by Haas et al. (2022) using a local sensitivity analysis approach, which is an approach investigating how different sources of uncertainty in an input can be separated and assigned to the output of a mathematical model or system, whether it is numerical or not. By focusing on the sensitivity around a set of factor values, local sensitivity analysis determines the local influence of input factor variation on model response.

Research questions to be addressed are summarised as follows: (1) is the index sensitive to changes in its construction focusing on various geographic scales; (2) how robust the SVIS is to changes in the subjective decisions made in developing the index algorithm; and (3) what the impact of changes in weighting and variables is set on the index results.

2 Methods and Data

The social vulnerability modelling approach assessed in this report is rooted in the work by Cutter et al. (2008) and has been adapted and applied in Sweden by Haas et al. (2022). To construct the index, Haas et al. (2022) derived a total of 16 variables related to social, demographic and economic parameters from the 2019 release of three sources, i.e. Statistics Sweden (SCB), the Swedish Public Employment Service (Arbetsförmedlingen), and the National Board of Health and Welfare (Socialstyrelsen). Haas et al. (2022) used Principal Component Analysis (PCA) resulting in four selected components that explain a total of 77.44 percent of the variance in the original dataset. These data were used to generate a Social Vulnerability Index (SVIS) for Sweden using equal weights.

To evaluate the robustness to changes in methodology, local-based sensitivity analysis, focusing on the sensitivity around a set of factor values to determine the local influence of input factor variation on model response, has been applied to the SVIS. Local sensitivity analysis evaluates the response of the output index to changes in one single construction stage by changing the options one at a time while other stages are kept constant (Chonggang Xu & George Zdzislaw Gertner, 2008). To evaluate the resilience of the index, the analysis has been performed using statistical tools/methods such as correlation (a method of assessing a possible two-way linear association between two continuous variables) and analysis of variance (a method measuring the data dispersion that takes into account the spread of all data points in a data set).

A positive correlation is a relationship between two variables that tend to move in the same direction, while two variables are negative correlated if they change in opposite directions.

The parameters employed for the local sensitivity analysis in this study are presented in Table 1. In the following section, different test employed to show the sensitivity of the resulting SVIS are presented and described in detail.

Table 1. Sensitivity analysis options.

Index stage	Options	
Scale of the analysis	Municipality level	RegSo level
Factor retention	Kaiser criterion	Parallel analysis
Weigting	Equal	Expert (workshop)
Indicator set	Basic {Haas, 2022 #560}	Alternative scenarios (workshop)

2.1 Test 1: Scale of analysis

The impact of changing aggregation scale levels on the analysis was assessed using an approach first presented by Clark and Avery (1976) and later applied in the context of natural hazards by Schmidtlein et al. (2008). In both studies, the correlations between variables were calculated for the same data and study area at multiple scales. As a result, if the level of aggregation increases, then the correlation between variables also increases. While this did not give insight into the extent of the problem created by the initial aggregation of observation units, it did provide a method to assess the impact of the fallacy on subsequent changes in aggregation scales. Combining the assessment of changing scales with an explicit limitation of the application of analytical results to the scale at which they were derived provides a simple means of addressing the impact of the scale issue on calculating a social vulnerability index at various aggregation levels. The problem then reduces to the choice of an appropriate scale of analysis (Schmidtlein et al., 2008). A second issue is that the relationships between spatially aggregated variables may result as much from the aggregation scheme as from the fundamental relationships between the variables themselves. Indeed, considerable differences in correlations between variables may be produced by changing the aggregation scheme (Openshaw, 1983), which is called the Modifiable Areal Unit Problem (MAUP). This demands to apply results from analysis of spatial data only to the study units at which they were conducted. Short of creating new aggregation units, the problem here becomes one of determining whether the study units used in an analysis are truly meaningful.

To assess the importance of scale of the analysis, the approach included an analysis at municipality level (n=290 units) and Regso level (n=3363 units). This was done to determine whether a given area has the same level of social vulnerability if analysed at different geographical scales. Indices at different scales were constructed and produced PCA results were compared.

Furthermore, focusing on a region, index scores were computed at RegSo level and averaged within each municipality. The produced ranks were then compared with those originally analysed at the municipality level.

2.2 Test 2: Factor retention

The second test in our sensitivity analysis considered the influence of different options in the construction of the index. Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. A common rationale behind factor analytic methods is that the information gained about the interdependencies between observed variables can be used later to reduce the set of variables in a dataset. It may help to deal with data sets where there are large numbers of observed variables that are thought to reflect a smaller number of underlying/latent variables.

When creating a vulnerability index, one key decision is how many components to recall from the Principal Component Analysis (PCA). In general, factor analysts would like to retain factors until additional factors account for trivial variance; however, different methods of specifying the number of factors to retain often lead to different solutions (Hayton et al., 2004). To determine the impact of factor retention option two different methods are commonly used to statistically assess changes in the SVIS: the Kaiser criterion and Parallel analysis.

Kaiser (greater than 1) criterion is one of the most commonly used methods, which retains factors with related eigenvalues greater than 1 (Kaiser, 1960) and this is the default retention criterion for a number of statistical packages (e.g., SPSS, SAS).

Another factor retention method is Parallel analysis (Horn, 1965). This selection criterion is similar to the Kaiser criterion and attempts to overcome a primary limitation: the overestimation of matrix ranks due to the sampling error (Hayton et al., 2004)[1].

Parallel analysis involves constructing a number of correlation matrices of random variables based on the same sample size and number of variables in the real data set. The averaged eigenvalues from the random correlation matrices are then compared to the eigenvalues from the real data correlation matrix, such that the first observed eigenvalue is compared to the first random eigenvalue, the second

[1] Kaiser criterion is based on an assumed population correlation matrix and is appropriate only as the sample size approaches infinity (Glorfeld, L. W., 1995). In a population matrix, the eigenvalues for random or mutually uncorrelated variables would equal 1. However, in a finite sample, sampling error and least-squares bias lead initial eigenvalues to be greater than 1 and later eigenvalues to be less than 1 (Horn, J. L., 1965; Turner, N. E., 1998). This means that for finite samples, some factors with eigenvalues greater than 1 may occur purely as a result of sampling error. Parallel analysis adjusts for the effect of sampling error and therefore is a sample-based alternative to the population-based Kaiser criterion (Carraher, S. M., & Buckley, M. R., 1991; Zwick, W. R., & Velicer, W. F., 1982).

observed eigenvalue is compared to the second random eigenvalue, and so on (Hayton et al., 2004). Finally, components with real data eigenvalues greater than the random eigenvalues are chosen for the PCA. Within this study, parallel analysis was based on 1000 randomly generated data sets on which PCA was performed and then averages over the resulting eigenvalues were computed.

2.3 Test 3: Weighting

When considering the factors that contribute to social vulnerability, it is vital to recognize that the weight or importance of each factor can vary depending on the context and the specific characteristics being considered. It is important to assess and consider the unique characteristics of factors when evaluating their social vulnerability and developing strategies for addressing it. Within this study, two options in terms the weighting of each involved parameter were considered. First, an equal weighting for all parameters approach was followed, as presented by Haas et al. (2022), and then, an unequal weighting based on expert opinion was applied.

The expert weights were derived during a workshop where scientists and professionals participated to determine the level of importance for the different components resulting from the PCA. The purpose of the workshop was to: (1) evaluate indicators and factors of the Social Vulnerability Index (SVIS) developed by Haas et al. (2022) based on expert perception and experiences; and (2) provide further indicators that contribute to the overall measure of social vulnerability in Sweden.

2.4 Test 4: Variables set

Another sensitivity test was applied with a reduced set of variables to examine the behaviour of the model on SVIS construction. To determine the effect of using a different set of variables, workshop participants were asked to debate the inclusion/exclusion of variables into the final composite index. Indices with different sets of variables were constructed and PCA results were compared.

3 Results

3.1 Test 1: Scale of analysis

To assess both effects in the Swedish case study, social vulnerability indices were constructed and compared at municipality and RegSo levels after using PCA.

PCA results conducted at different scales of aggregation levels are presented in Table 2. In accordance with the studies by Clark and Avery (1976) and Schmidtlein et al. (2008), as the scale of aggregation at which the PCA was conducted decreased (municipality to RegSo), the variance explained slightly decreased from 77.43 percent (Municipality level) to 76.81 percent (RegSo level).

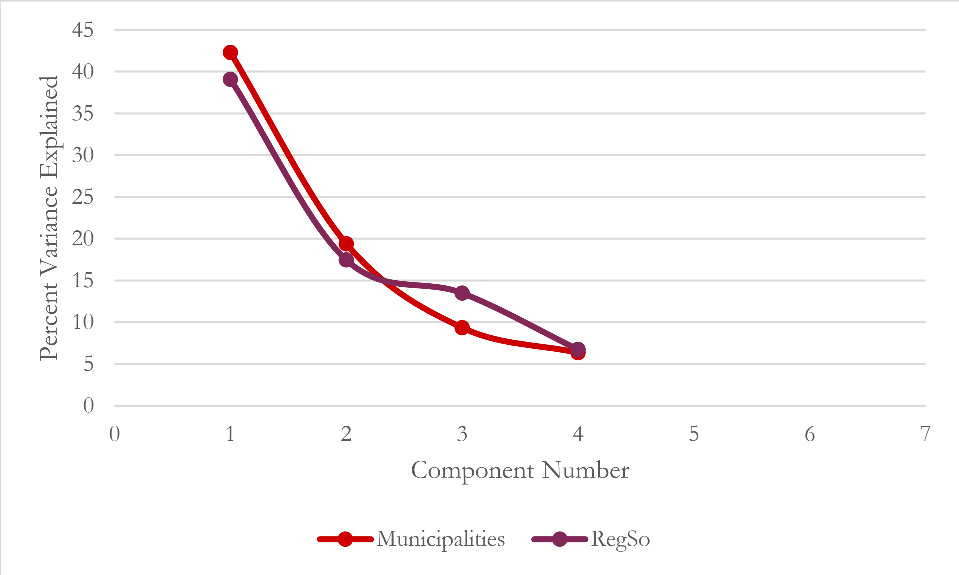
The four components are shown in Table 2 in a decreasing order according to the percentage of the variance explained. For each component, the variables are provided in a decreasing order of correlation.

Table 2. Results for Municipality and RegSo Level PCA

	Municipality level	RegSo level
Number of components	4	4
Variance explained (%)	77.439	76.81
Components interpretation	**Component 1** (42.306)	**Component 1** (39.111)
(% variance explained)	Population 0-14	Low economic standard
	Household size	No high school education
	Population 75+	Economic support
	Population change	Median income
	Single household with children	Long term unemployed
	Median income	Reduced capacity to work
		Living in rented apartment
		Outside EU born (less than 3 years in Sweden)
		High economic standard
		Single household with children
	Component 2 (19.418)	**Component 2** (17.468)
	Urban area	Population 0-14
	Building per Km²	Household size
	High economic standard	Population 75+
	Reduced capacity to work	
	Component 3 (9.356)	**Component 3** (13.492)
	Outside EU born (less than 3 years in Sweden)	Urban area
	Low economic standard	Building per Km²
	No high school education	
	Economic support	
	Component 4 (6.358)	**Component 4** (6.739)
	Living in rented apartment	Population change
	Long term unemployed	

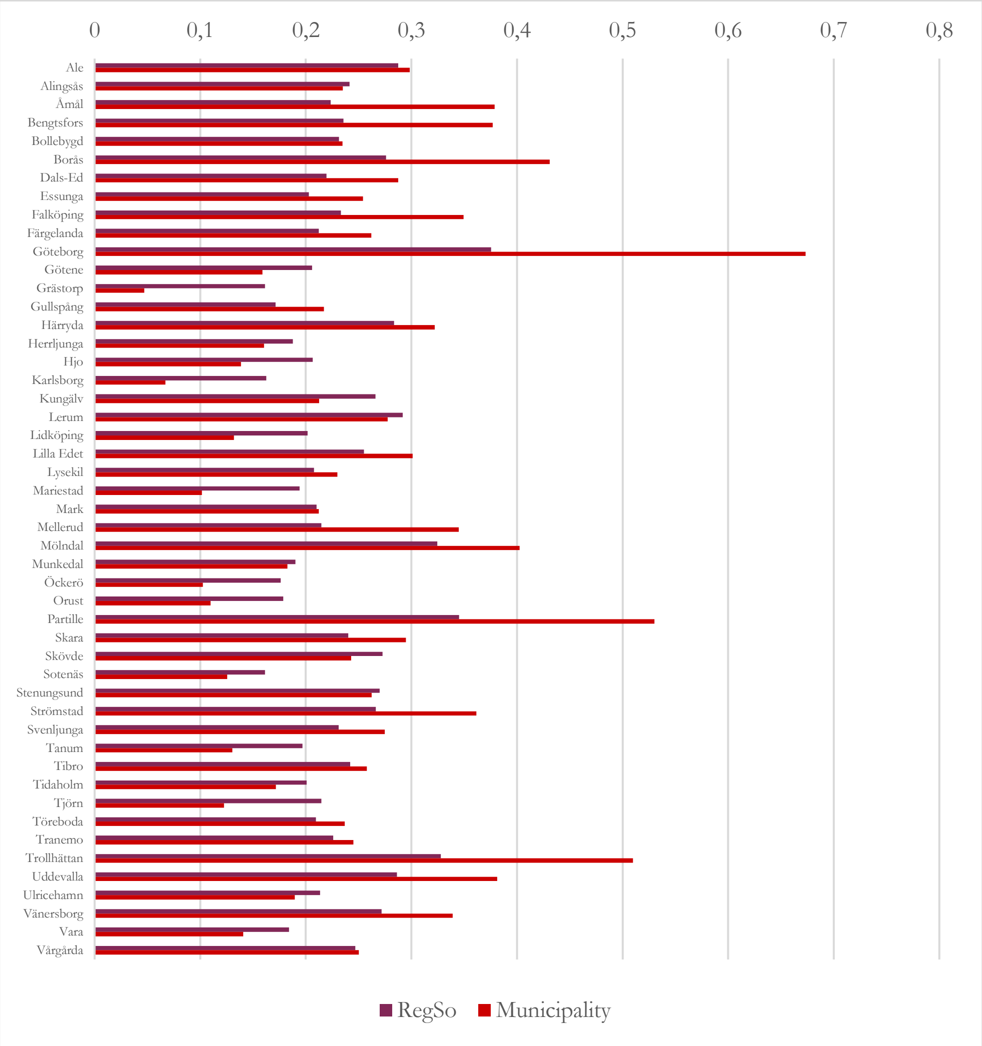
Figure 1 shows a graph of the percentage of variance explained by the components selected for different scales of analysis. It is shown that decreasing the level of aggregation leads to lower values of the variance explained for the two first components. The third and fourth components follow a reverse order, that is decreasing the level of aggregation leads to the increase of the variance presented. This is explained by the fact that Component 3 (RegSo) variables seem to contribute more to the evaluation of variance as it is evident from Component 2 (municipality) variables (Table 2). For Component 4 a similar documentation applies.

Figure 1. Variance explained by component for two aggregation levels (Municipality level and RegSo level)



In Figure 2, index scores for municipalities and averaged RegSo scores within each municipality are presented for Västa Götaland region.

Figure 2. SVIS scores for municipalities and averaged RegSo scores within each municipality for Västa Götaland region.



SVIS on the municipal level indicates that Göteborg (this example) has the highest values, followed by the municipalities of Partille and Trollhättan. As a result, Göteborg municipality (if hazard-exposed) would (from an economic point of view) receive higher investments in vulnerability reduction than the other municipalities, followed by the municipalities of Partille and Trollhättan.

If compared to Figure 3[2] it becomes evident that not the entire municipality of Göteborg is "vulnerable", but only certain districts are. As a result, RegSo provides higher resolution in-depth information on social vulnerability, even if it is acknowledged that because of the PCA, components and their variables are slightly different (cf. Table 2). In any case, a comparison between municipalities and RegSo level is possible. As shown in Figure 3, social vulnerability is context-specific and highly variable over smaller spatial entities which allows the fund providers to explicitly address these RegSo units with highest vulnerability values

[2] Please, be aware that this is a zoom-in of the entire country and values refer to the whole Sweden

in risk management by e.g. prioritising investments in an economically efficient way.

The same is valid for the entire area of interest, if compared between Figures 3 and 4: larger parts of the Västa Götaland areas are composed of municipalities with high vulnerability values, however, it is only distinct local areas (high resolution) with high vulnerability values (red colour scheme) and vice versa for low vulnerability (blue colour scheme). To summarise, only very few (RegSo) areas have a high social vulnerability, these are located spot-wise over the entire study area.

Figure 3. SVIS for municipality level in Västa Götaland

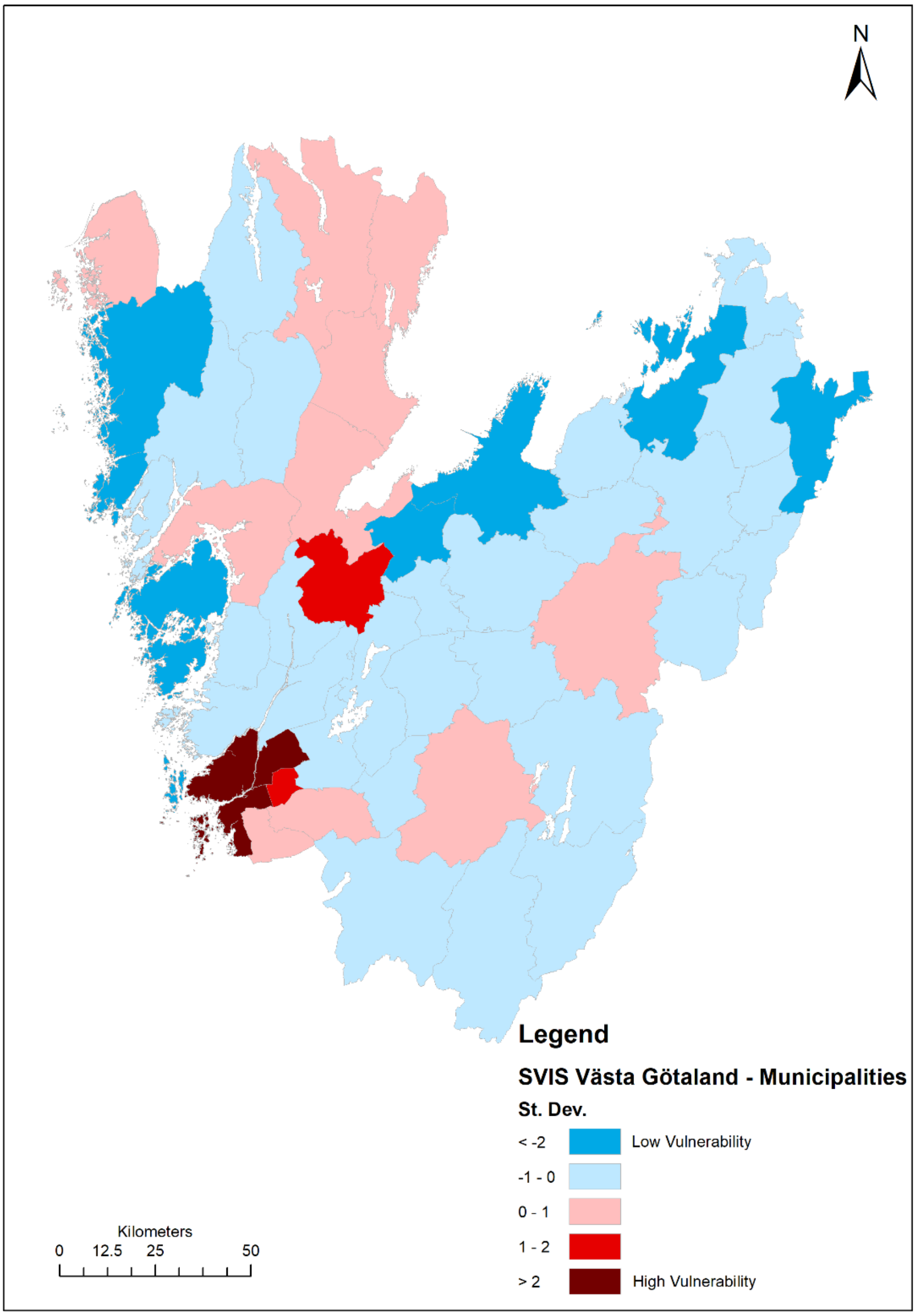
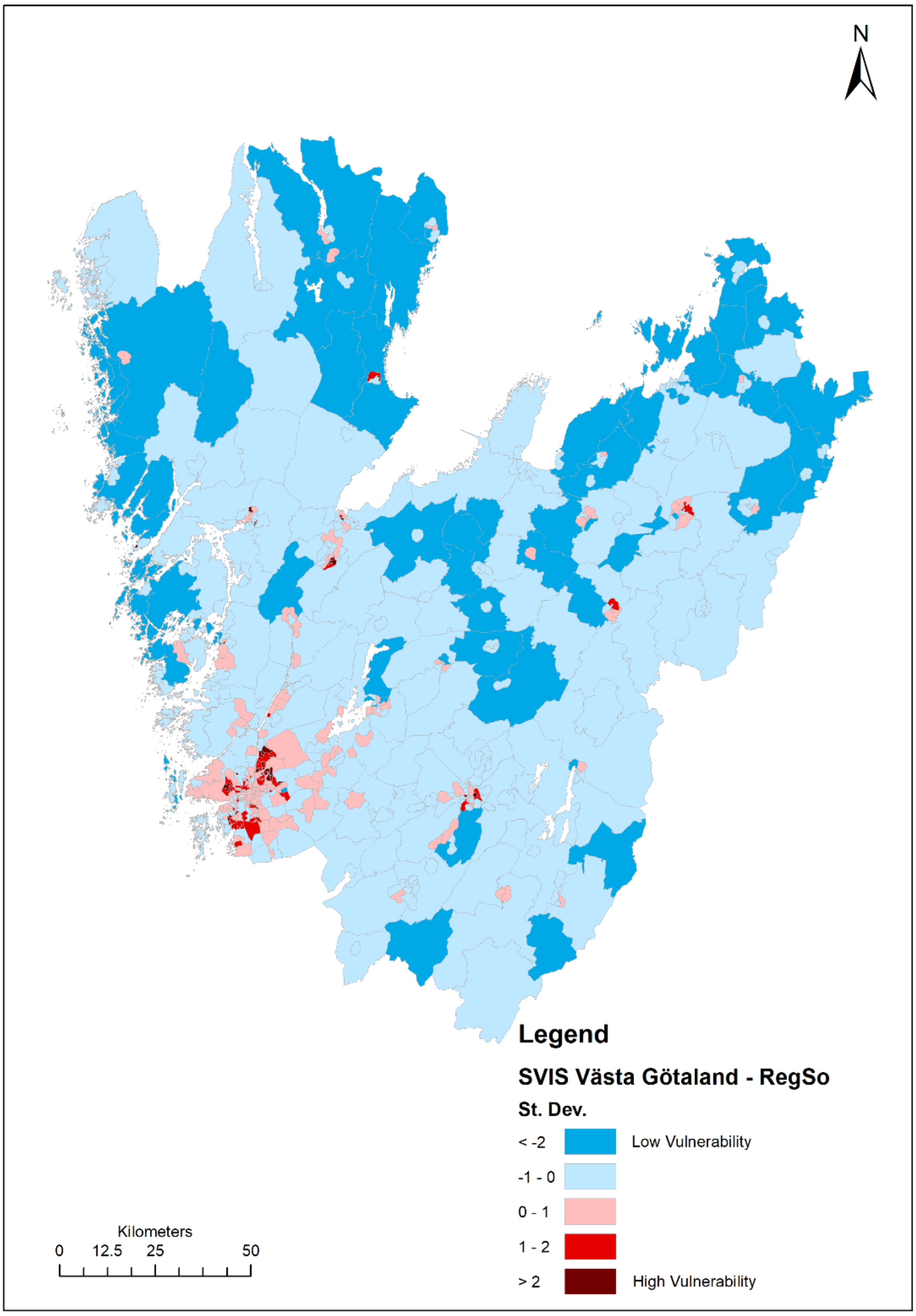


Figure 4. SVIS for RegSo level in Västa Götaland

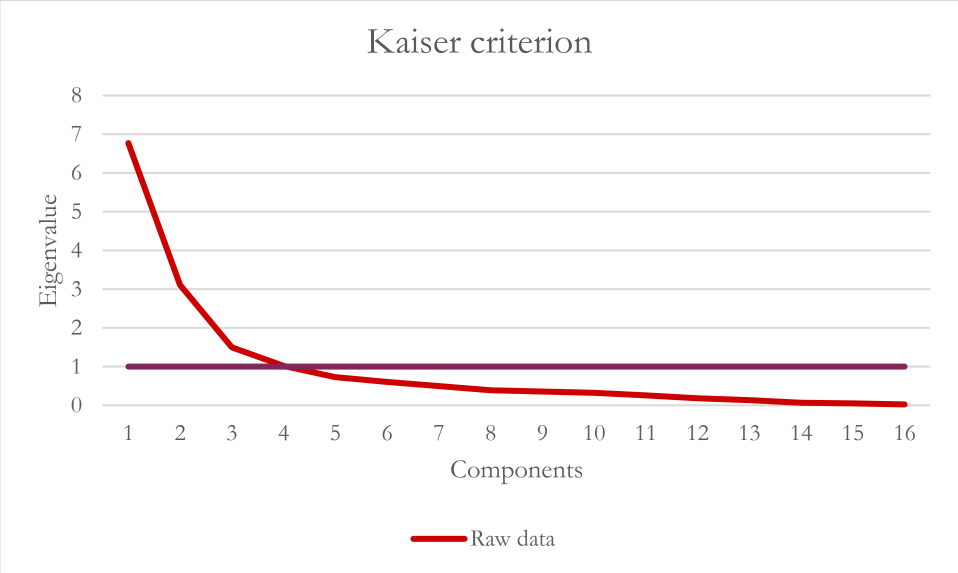


3.2 Test 2: Factor retention (Kaiser criterion – Parallel analysis

3.2.1 Kaiser criterion

Figure 5 illustrates the results of the computation of the Kaiser criterion. In particular, it is showing the distribution of eigenvalues for each component around the threshold line 1 (purple line). Based on the eigenvalues analysis provided by Kaiser criterion only four components were selected for the respective case study. For more details, please refer to Table 4.

Figure 5. Kaiser criterion scree plot



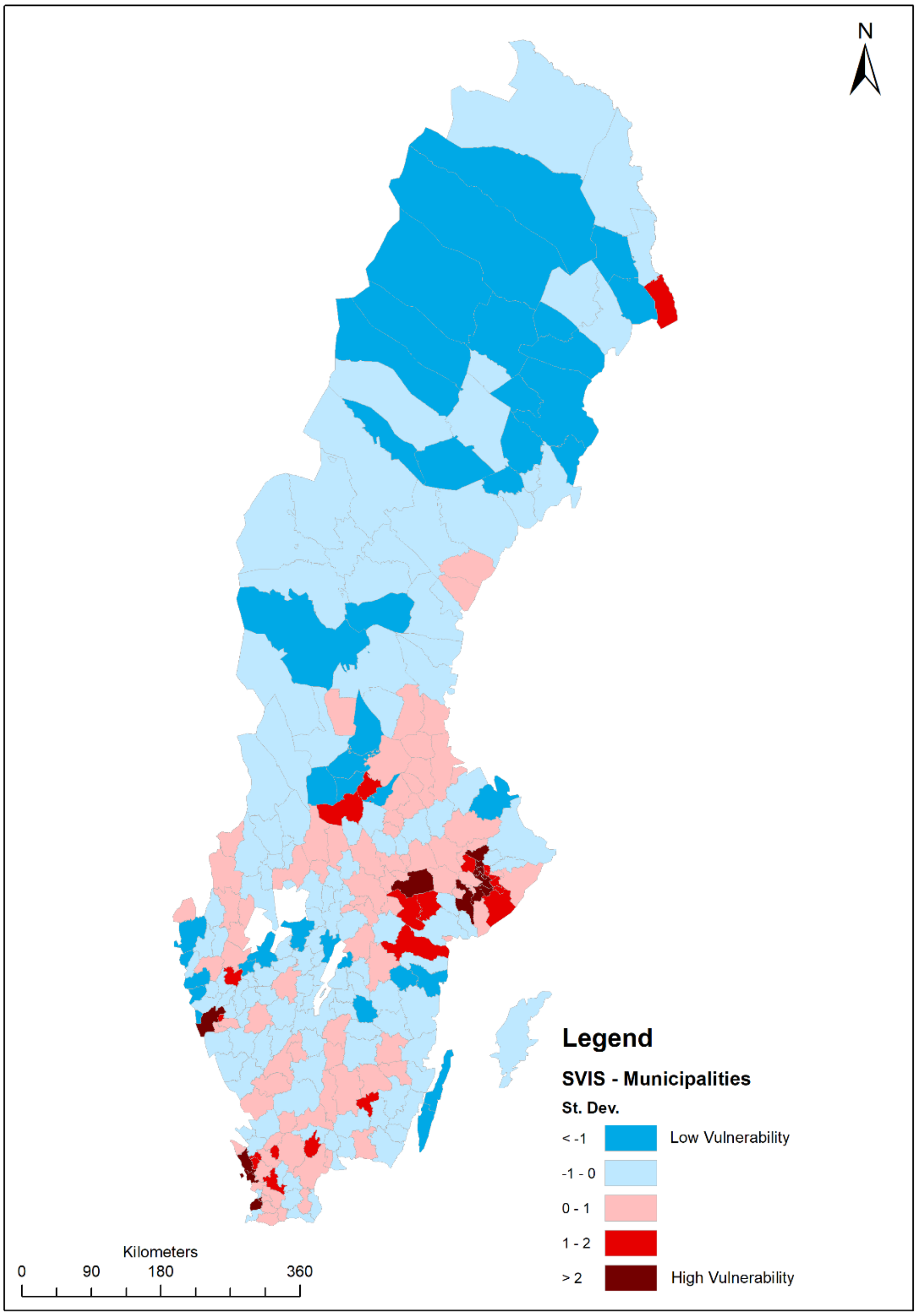
The PCA analysis following the Kaiser criterion (four components) allowed to explain 77.44 percent of the total variance among the Swedish municipalities. Each of the components was able to explain between 6.4 and 42.3 percent of the total variance. The dominant variables for each retaining component are presented in Table 3.

Table 3. SVIS components and variable loadings at the municipality level, constructed based on Kaiser criterion.

Variables	Component			
	1	2	3	4
Population 0 to 14 perc	0.924			
Household size	0.893			
Population 75 plus	-0.846			
Population change	0.624			
Single household with children	0.597			
Median income	0.584			
Urban area		0.885		
Buildings per Km²		0.871		
High economic standard		0.781		
Reduced capacity to work		-0.577		
Outside EU born (less than 3 years in Sweden)			0.825	
Low economic standard			0.746	
No high school			0.708	
Economic support			0.613	
Living In rented apartment				0.886
Long term unemployed				0.610

Figure 6 depicts the combined vulnerability considering all four principal components constructed on the original approach (Kaiser criterion). The legend classes are based on a bipolar classification scheme. This classification method is based on the mean and the standard deviation and shows the extent of deviation of the feature attribute values from the mean. Data below the average is given in blue colours and data above the average in red colours. Class breaks are applied using the respective standard deviation from mean. As a result, blue colour characterises municipalities of low social vulnerability values and red colour municipalities with high social vulnerability values.

Figure 6. SVIS at the municipality level, constructed to the original approach (Kaiser criterion).



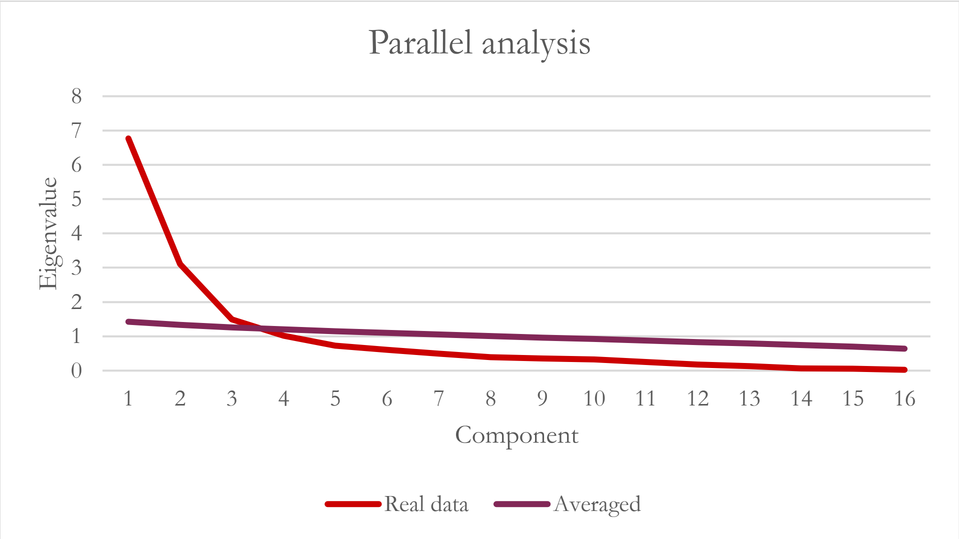
3.2.2 Parallel analysis

Table 4 presents eigenvalues related to the original data set in relation to the averaged eigenvalues of the 1000 randomly generated data sets. Based on parallel analysis results, three factors should be selected for the respected case study. Figure 7 illustrates the real data and the average eigenvalues of the 1000 randomly generated data sets.

Table 4. Parallel analysis eigenvalues

Component	Eigenvalues	
	Real data	Averaged
1	6.769013	1.4251
2	3.106949	1.333119
3	1.497013	1.263091
4	1.017279	1.201303
5	0.726898	1.147956
6	0.604095	1.099271
7	0.496068	1.052028
8	0.389473	1.007476
9	0.357843	0.963551
10	0.321875	0.921177
11	0.255704	0.878024
12	0.180439	0.834818
13	0.130224	0.791065
14	0.068547	0.745496
15	0.054689	0.696564
16	0.02389	0.639961

Figure 7. Parallel analysis scree plot.



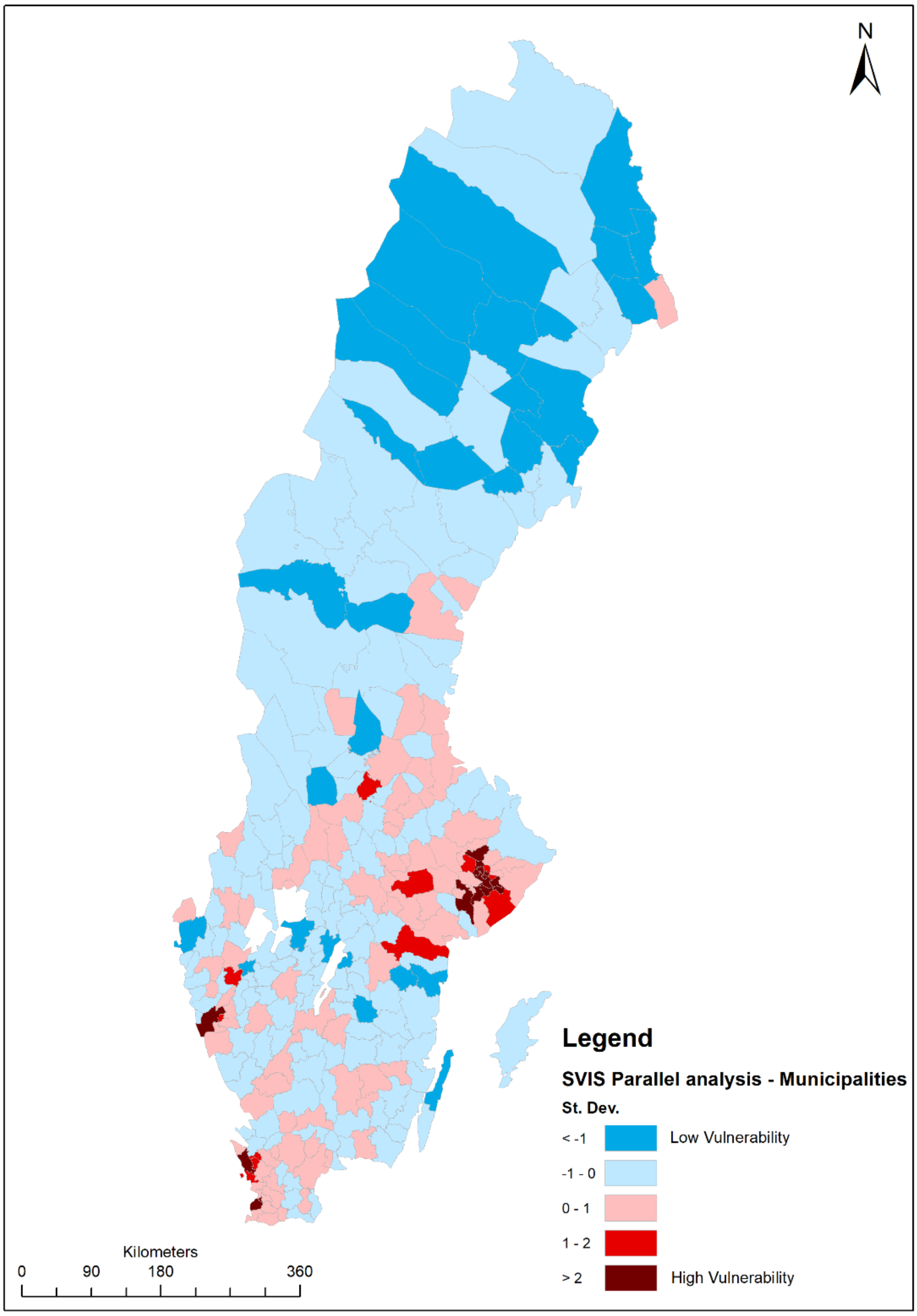
According to Table 4 results of parallel analysis indicate that three components should be chosen for the PCA. The PCA analysis following parallel analysis (three components) explain 71.08 percent of the total variance among the Swedish municipalities. Each of the components explains between 9.3 and 42.03 percent of the total variance. The dominant variables for each retaining component are presented in Table 5.

Table 5. SVIS components and variable loadings at the municipality level, constructed based on parallel analysis results.

Variables	Component		
	1	2	3
Population 0 to 14	0.914		
Population 75+	-0.881		
Household size	0.871		
Population change	0.689		
Median income	0.617		
Single household with child	0.606		
Urban area		0.883	
Buildings per Km^2		0.859	
High economic standard		0.783	
Reduced capacity to work		-0.584	
Long term unemployed			0.780
Low economic standard			0.687
Living in rented apartment			0.671
Outside EU born (less than 3 years in Sweden)			0.664
Economic support			0.656
No high school			0.617

Figure 8 shows the combined vulnerability considering all three principal components constructed using parallel analysis for the component selection. The legend classes are based on a bipolar classification scheme. Data below the average is given in blue colours and data above the average in red colour. As a result, blue colour characterises municipalities of low social vulnerability values and red colour municipalities with high social vulnerability values.

Figure 8. SVIS at the municipality level constructed using parallel analysis for the component selection.



3.3 Test 3: Weighting

3.3.1 Workshop results

In Figure 9, the professional background of the workshop participants is provided. A total of 20 persons attended the meeting at Karlstad University on 27th of October 2022, 42 percent of which coming from research, 38 percent from the public sector, and 10 percent each from the private sector and from other sectors. More than 63 percent of the participants have more than six years professional experience in the disaster community and more than 26 percent less than one year (Figure 10).

Figure 9. Professional background of the workshop participants.

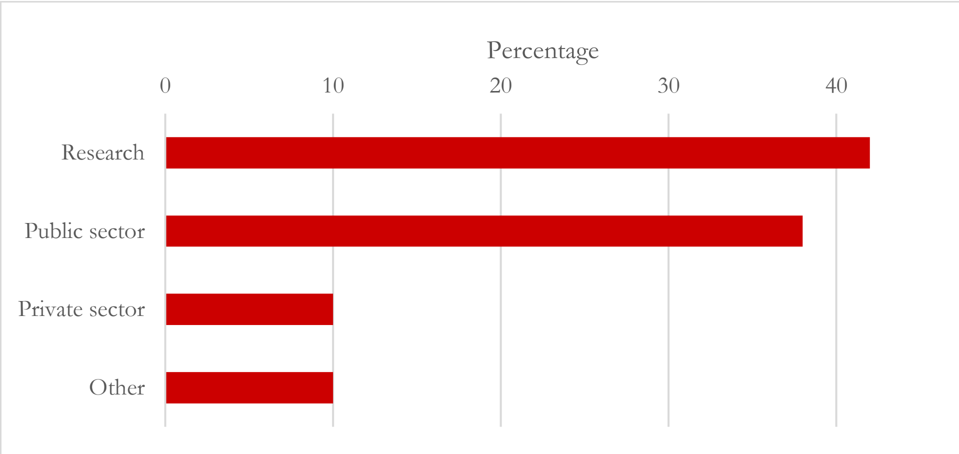
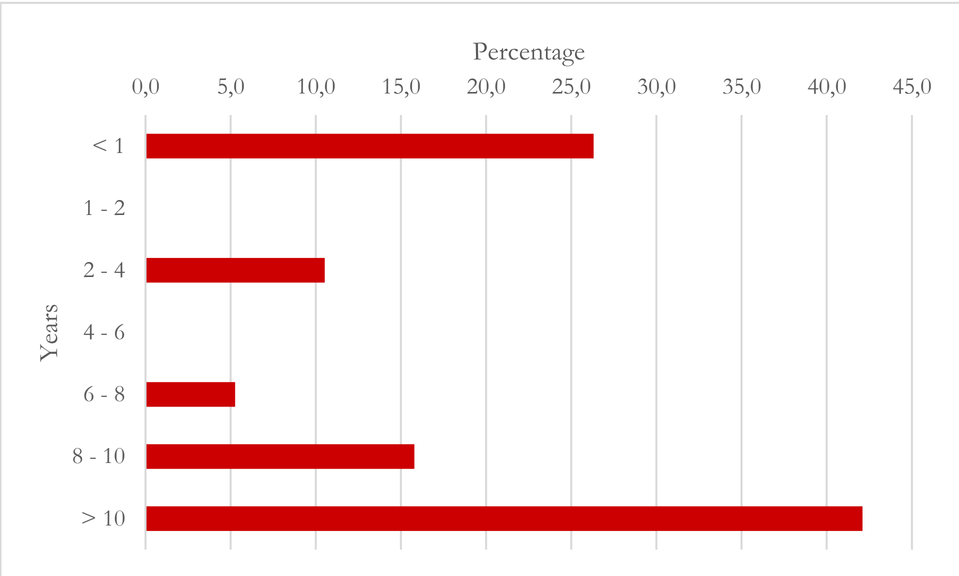
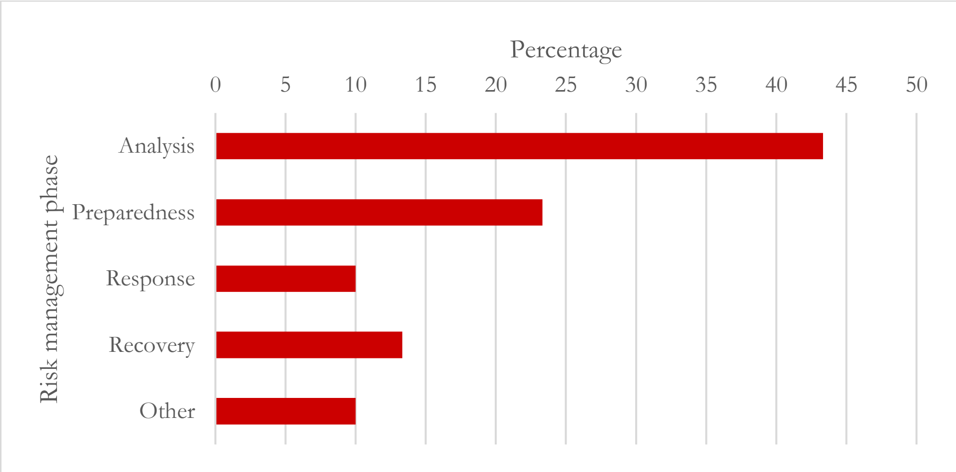


Figure 10. Years of experience for the workshop participants.



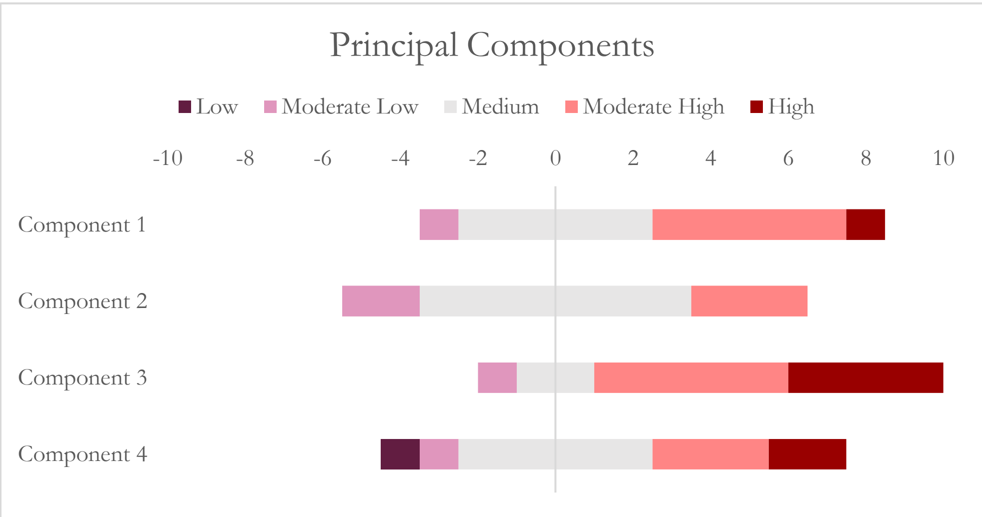
With respect to the different phases of risk management, 43 percent of the participants were related to the field of risk analysis followed by 23 percent to the field of preparedness, 10 percent to the field of response, 13 percent to the field of recovery and 10 percent to other fields (Figure 11).

Figure 11. Risk management phase that workshop participants involved.



Individuals were asked to rate the different components of the PCA according to the explanatory power for the social vulnerability index based on their individual professional experience. Component 3 was rated as the most important followed by components 1, 4 and 2 (Figure 12).

Figure 12. PCA components explanatory power based on participants' perception.



Subsequently, individuals were asked to assess the explanatory power of individual variables for every component separately. Results are provided in Figures 13 to 16.

Figure 13. Explanatory power of Component 1 variables based on the perception of participants.

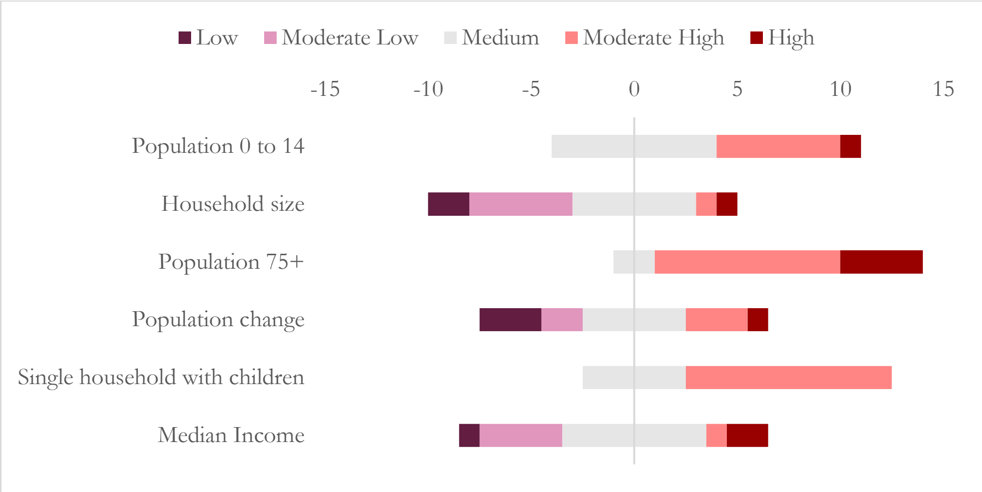


Figure 14. Component 2 variables explanatory power based on participants perception.

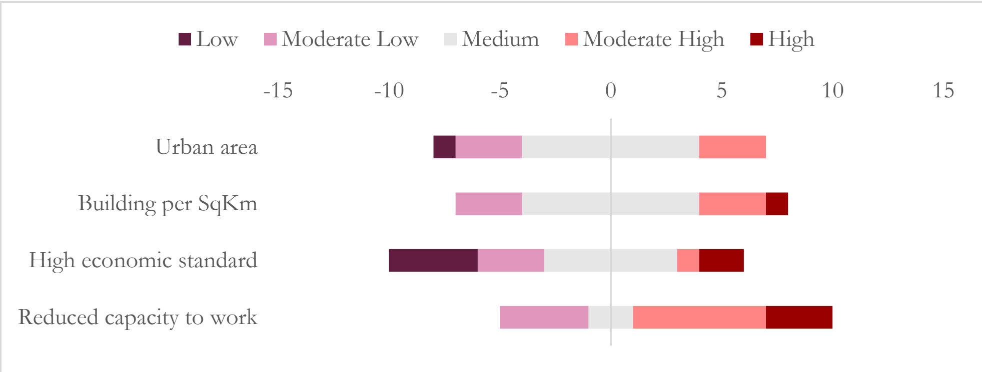


Figure 15. Component 3 variables explanatory power based on participants perception.

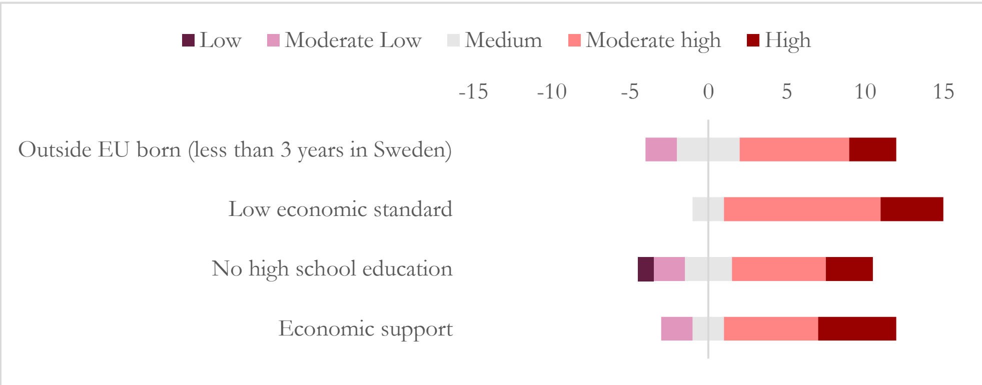
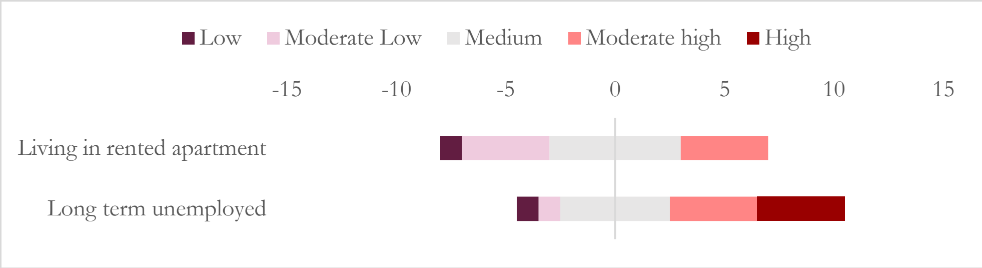


Figure 16. Component 4 variables explanatory power based on participants perception.



3.3.2 Weights

Based on expert knowledge gathered (see previous section) weights were calculated for the individual components. Table 6 shows that component 3 was the most important one with a weight of 0.39 followed by component 1 (0.26), component 4 (0.22) and component 2 (0.13). As a result, variables used to describe (a) a migration background and (b) a socially underprivileged part of the population received a higher relative ranking in comparison to other variables. In contrast, variables used to describe (a) an impact of land use planning together with (b) a high economic standard and (c) negatively correlated[3] – reduced capacities to work received lowest weighting for the overall social vulnerability index on municipality level.

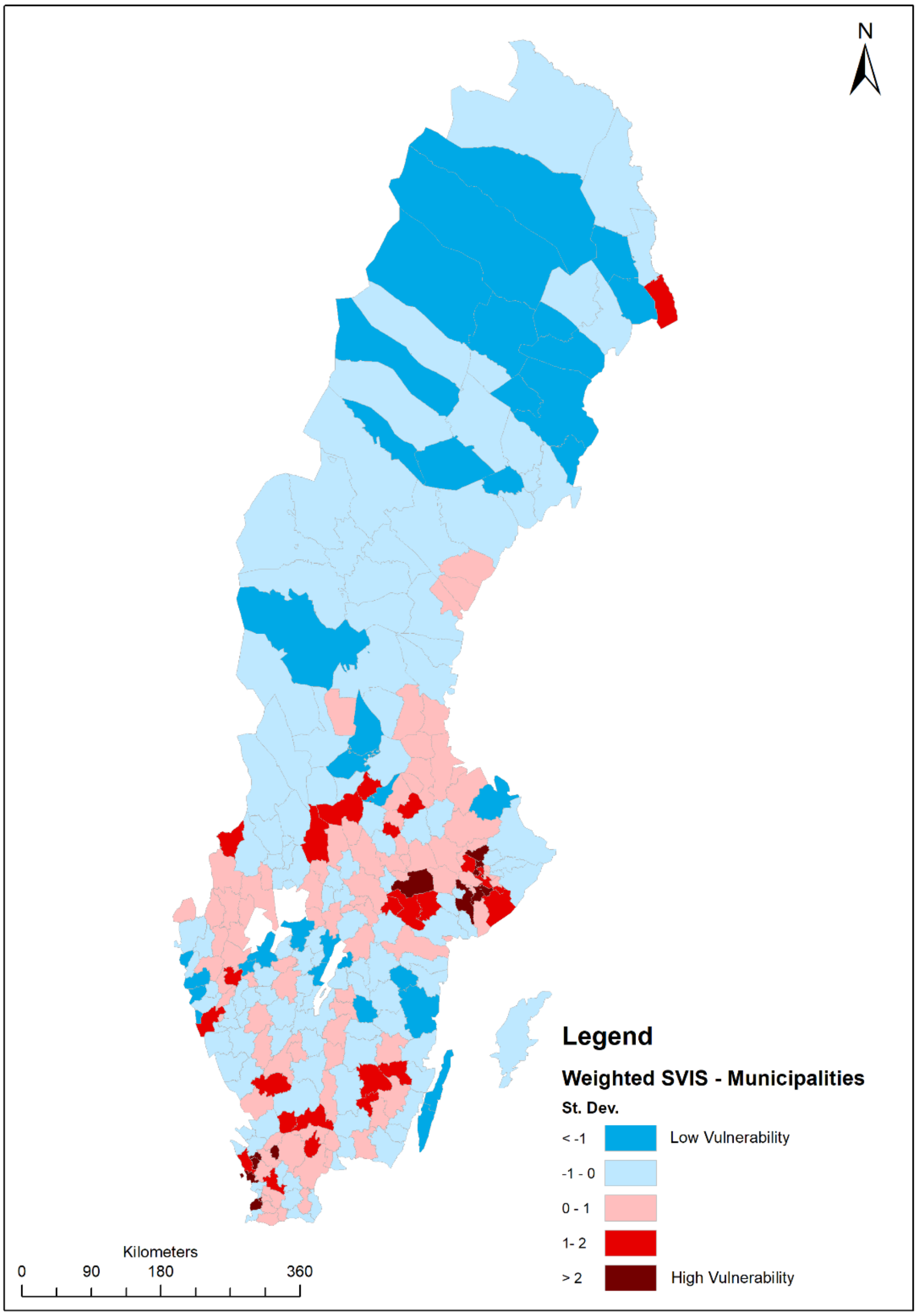
Table 6. Weights for the different components based on expert knowledge

Components	Weights
Component 1	0.26
Component 2	0.13
Component 3	0.39
Component 4	0.22

Figure 17 shows the combined vulnerability considering all four principal components constructed using expert knowledge weights for the aggregation of the components.

[3] A negative, or inverse, correlation between two variables indicates that one variable increases while the other decreases, and vice-versa. This relationship may or may not represent causation between the two variables, but it does describe an observable pattern.

Figure 17. SVIS at the municipality level, constructed to the original approach, using weighted sum components combination.



3.4 Test 4: Variables set

Based on workshop results, the variables "household size", "high economic standard" and "median income" were rated by the experts as having the least importance for the index construction. For that purpose, we examined how the SVIS is influenced if we exclude one of these at a time or all these variables simultaneously. For that purpose, we created three scenarios by leaving out each variable a time and one scenario where we left out all three variables (Table 7).

Table 7. SVIS different variable sets comparison

	Original SVIS (N = 16)	SVIS without "household size" variable (N = 15)	SVIS without "high economic standard" variable (N = 15)	SVIS without "median income" variable (N = 15)	SVIS without 3 variables (N = 13)
Components selected	4	3	3	4	3
Percentage variance explained	77.43	70.74	70.88	76.69	69.1
Components interpretation (percentage variance explained)	Component 1 (42.30)	Component 1 (41.10)	Component 1 (41.18)	Component 1 (39.51)	Component 1 (36.41)
	Component 2 (19.41)	Component 2 (20.61)	Component 2 (20.56)	Component 2 (20.42)	Component 2 (23.25)
	Component 3 (9.35)	Component 3 (9.03)	Component 3 (9.14)	Component 3 (9.97)	Component 3 (9.43)
	Component 4 (6.35)			Component 4 (6.78)	

In the next sub-chapters, the detailed results for every scenario are presented.

3.4.1 Scenario 1: Variable set without variable "household size"

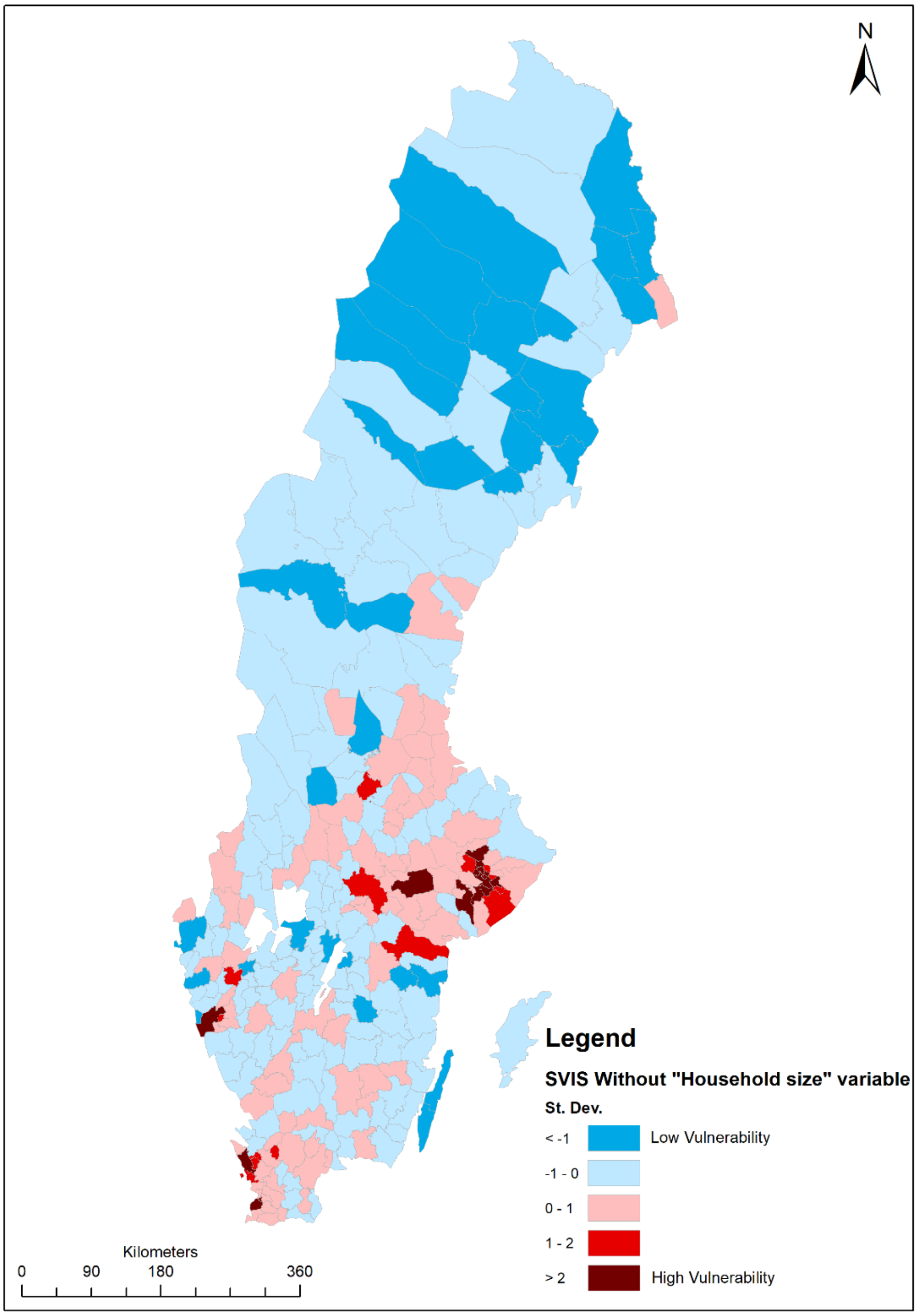
The PCA analysis retained three components, which explain the value 70.74 percent of the total variance among the Swedish municipalities. Each of the components contributes between 9.03 and 41.10 percent of the total variance. The dominant variables for each retaining component are presented in Table 8.

Table 8. SVIS components and variable loadings at the municipality level, constructed to the original approach, without the variable "household size".

Variables	Components		
	1	2	3
Population 75+	-0.898		
Population 0 to 14	0.841		
Population change	0.759		
Single household with child	0.607		
Median income	0.600		
Urban area		0.890	
Buildings per Km^2		0.883	
High economic standard		0.792	
Reduced capacity to work		-0.584	
Long term unemployed			0.758
Low economic standard			0.727
Outside EU born (less than 3 years in Sweden)			0.684
Economic support			0.676
No high school			0.656
Living in rented apartment			0.638

Figure 18 presents the combined vulnerability considering all three principal components constructed to the original approach, without the variable "household size".

Figure 18. SVIS at the municipality level, constructed to the original approach, without the variable “household size”.



3.4.2 Scenario 2: Variable set without variable “high-economic standard”

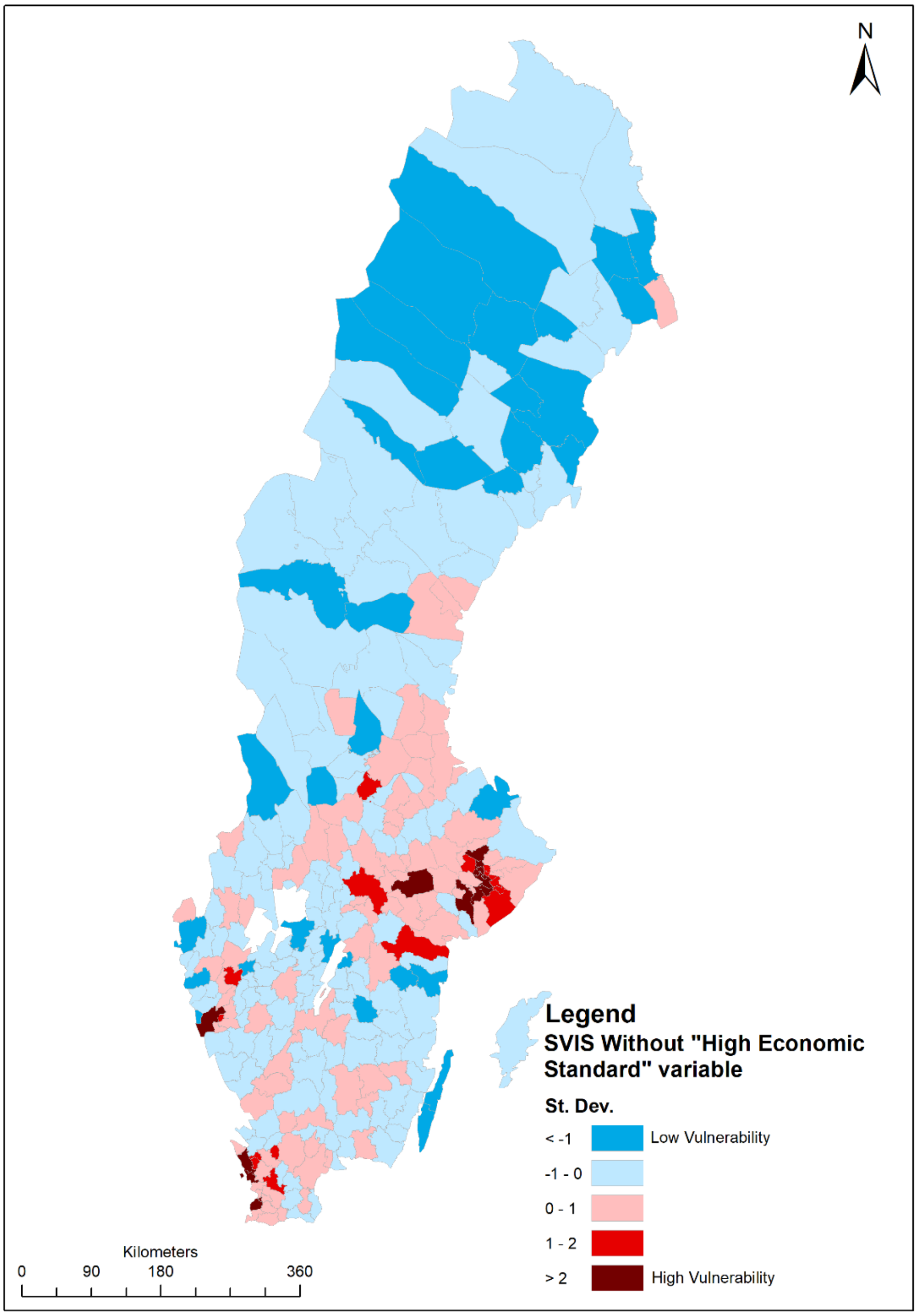
The PCA analysis retained three components, which explain the value 70.89 percent of the total variance among the Swedish municipalities. Each of the components contributes between 9.14 and 41.18 percent of the total variance. The dominant variables for each retaining component are presented in Table 9.

Table 9. SVIS components and variable loadings at the municipality level, constructed to the original approach, without the variable "high economic standard".

Variables	Component		
	1	2	3
Population 0 to 14	0.928		
Household size	0.896		
Population 75+	-0.876		
Population change	0.666		
Median income	0.639		
Single household with child	0.612		
Long term unemployed		0.756	
Low economic standard		0.725	
Economic support		0.692	
No high school		0.676	
Outside EU born (less than 3 years in Sweden)		0.663	
Living in rented apartment		0.654	
Urban area			0.897
Buildings per Km²			0.849
Reduced capacity to work			-0.523

Figure 19 presents the combined vulnerability considering all three principal components constructed to the original approach, without the variable "high economic standard".

Figure 19. SVIS at the municipality level, constructed to the original approach, without the variable “high economic standard”.



3.4.3 Scenario 3: Variable set without variable "median income"

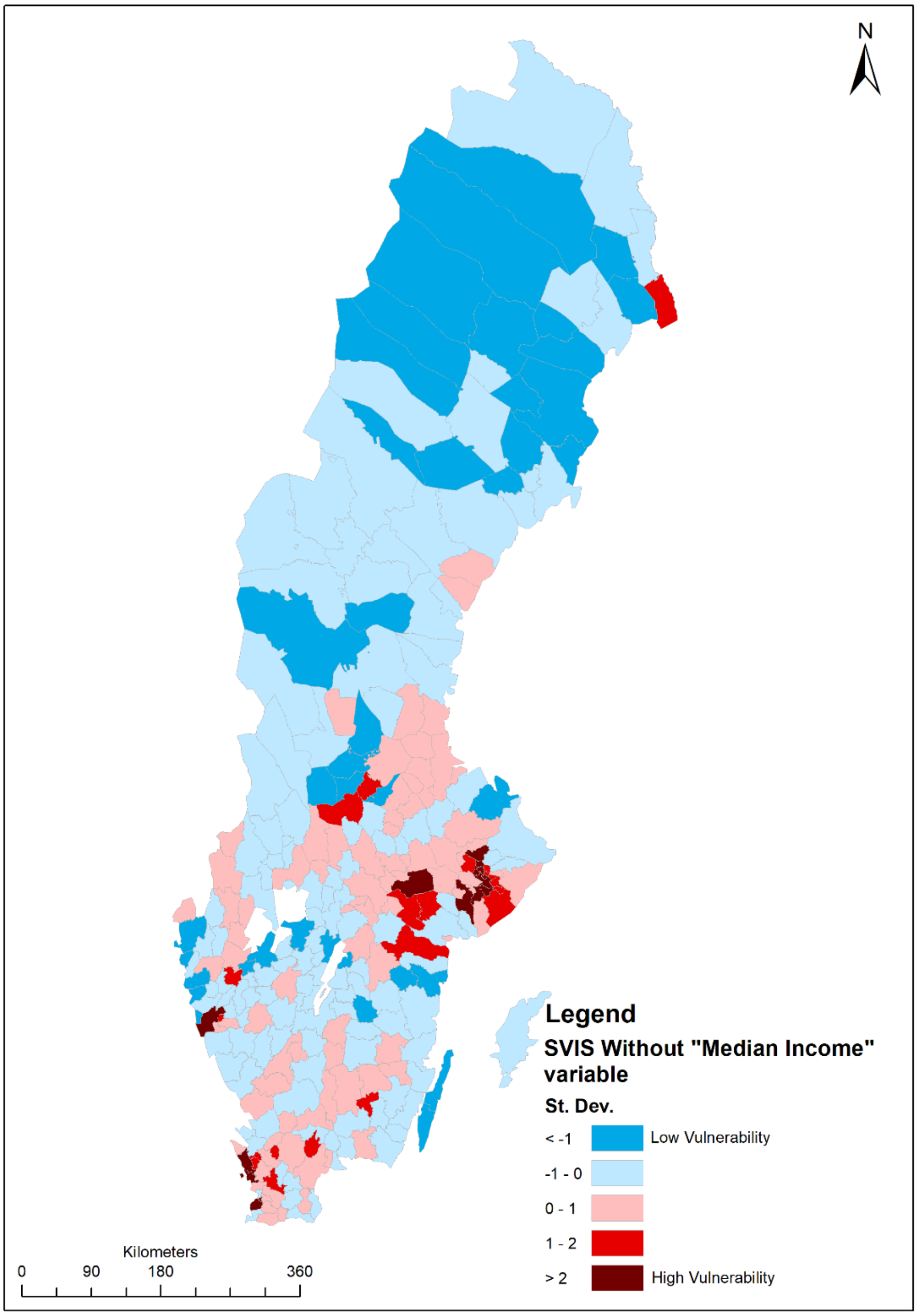
The PCA analysis retained four components, which explain the value 76.69 percent of the total variance among the Swedish municipalities. Each of the components contributes between 6.781 and 39.51 percent of the total variance. The dominant variables for each retaining component are presented in Table 10.

Table 10. SVIS components and variable loadings at the municipality level, constructed to the original approach, without the variable "median income".

Variables	Components			
	1	2	3	4
Population 0 to 14	0.922			
Household size	0.891			
Population 75+	-0.848			
Population change	0.634			
Single household with child	0.601			
Urban area		0.887		
Buildings per Km²		0.874		
High economic standard		0.778		
Reduced capacity to work		-0.578		
Outside EU born (less than 3 years in Sweden)			0.828	
Low economic standard			0.739	
No high school			0.706	
Economic support			0.621	
Living in rented apartment				0.889
Long term unemployed				0.606

Figure 20 presents the combined vulnerability considering all four principal components constructed to the original approach, without the variable "median income".

Figure 20. SVIS at the municipality level, constructed to the original approach, without the variable “median income”.



3.4.4 Scenario 4: Variable set without the variables “household size”, “high economic standard” and “median income”

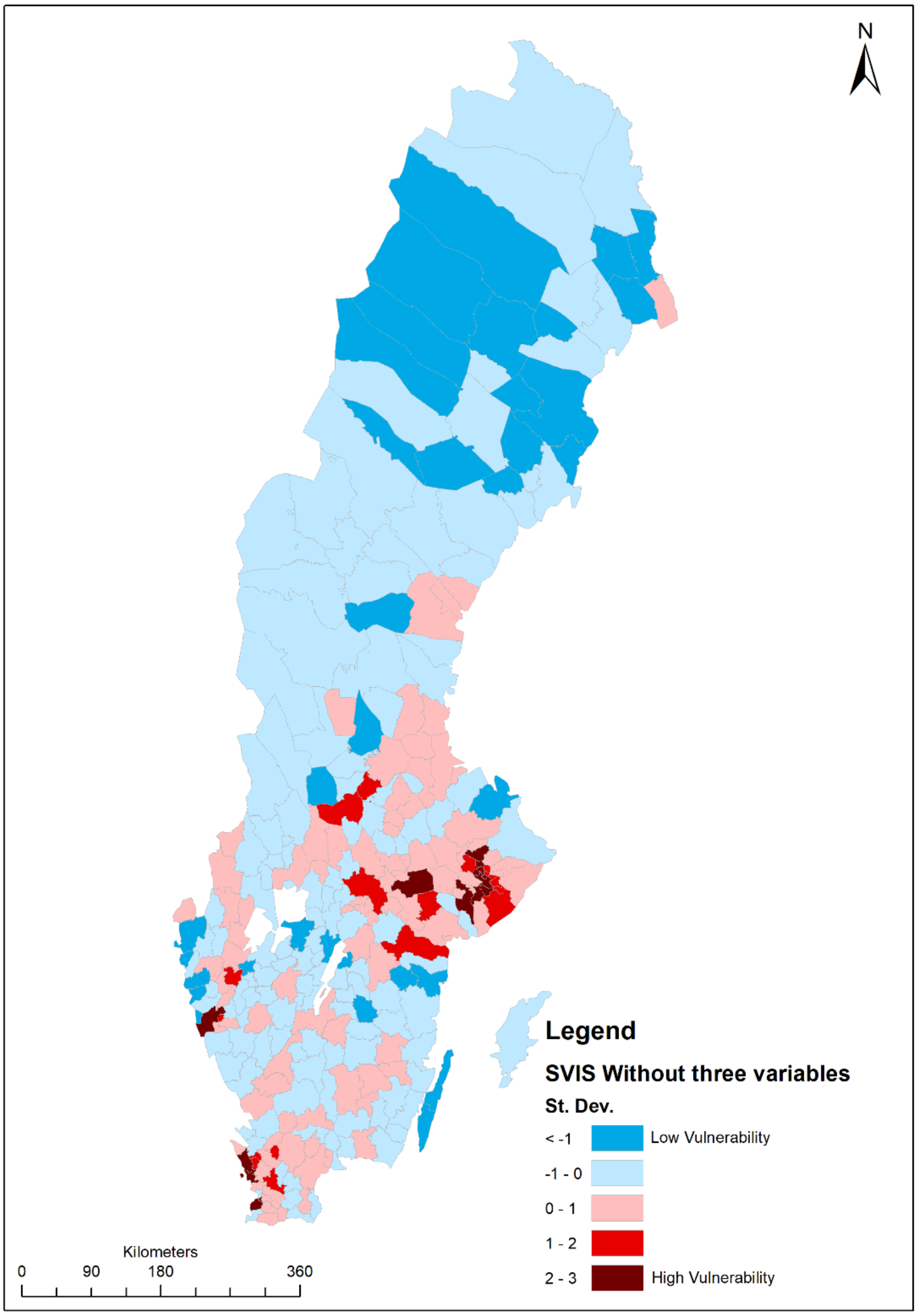
The PCA analysis retained three components, which explain the value 69.10 percent of the total variance among the Swedish municipalities. Each of the components contributes between 9.435 and 36.41 percent of the total variance. The dominant variables for each retaining component are presented in Table 11.

Table 11. SVIS components and variable loadings at the municipality level, constructed to the original approach, without the variables “household size”, “high economic standard” and “median income”

Variables	Components		
	1	2	3
Population 75+	-0.901		
Population 0 to 14	0.854		
Population change	0.762		
Single household with child	0.619		
Low economic standard		0.750	
Long term unemployed		0.728	
Economic support		0.718	
No high school		0.701	
Outside EU born (less than 3 years in Sweden)		0.678	
Living in rented apartment		0.635	
Urban area			0.914
Buildings per Km²			0.887
Reduced capacity to work			-0.529

Figure 21 presents the combined vulnerability considering all three principal components constructed to the original approach, without the variables “household size”, “high economic standard” and “median income”.

Figure 21. SVIS at the municipality level, constructed to the original approach, without the variables "household size", "high economic standard" and "median income"



4 Conclusions/ Recommendations

There is a growing concern in the DRR community that efforts to reduce adverse impacts of multiple hazard types have to include social dimensions to reduce uncertainties in the accuracy of hazard mitigation and adaptation. In contrast, there is a mismatch observable between the growing number of studies on social vulnerability and related assessments and the understanding of their empirical validity. Considering this, the purpose of this study was to systematically evaluate the Social Vulnerability Index (SVIS) developed by Haas et al. (2022) using a local sensitivity analysis approach.

Based on our analysis the main findings and recommendations are summarized as follows:

- *Scale of the analysis*: Regarding the effect of scale changes on the assessment results, the subjective interpretation of the PCA components remained stable across different scales. Notably, as the scale of aggregation at which the PCA was conducted decreased (from municipality to RegSo), the variables variance decreased as well, which is in accordance with similar approaches available in the literature. Indeed, the RegSo level provides higher resolution and in-depth information on social vulnerability, even if due to the PCA variables in the different components are slightly different. Overall, the SVIS algorithm seems robust to changes if applied to multiple scales. Both analyses could be used for future implementations. Additional local knowledge will support the interpretation of the results.

- *Factor retention*: The second test in our sensitivity analysis considered the influence of different options in the construction of the index. Regarding the factor retention method used (i.e. how many components to recall from the PCA) the results showed considerable differences. The Kaiser criterion (four components for the PCA) appeared different from the parallel analysis (three components for the PCA). We suggest using the Kaiser criterion due to the higher variance explained by the algorithm in the respective case study. Parallel analysis indicated that three components should be chosen for the PCA. The experts invited to provide input (workshop), however, rated the fourth component as important. In this line, it is not recommended to exclude the fourth component. Furthermore, as discussed in the previous chapters, the Kaiser criterion is the default retention method for a number of statistical packages. Therefore, it is easier to be implemented in any future reproduction of the index.

- *Weighting*: When weighing the weight of the components supporting the SVIS index it is important to understand that the weight of each component varies depending on the context and the specific characteristics considered. In this study, two different options (expert knowledge and equal weights) were tested, and the effect of the weights had a significant impact on the formation of the index. The results appear quite different (Figure 17 and Figure 18) in each case and local knowledge could support the interpretation of the results in a more comprehensive way. Further research should be conducted to better understand the implications of applying weights at the index construction.
- *Indicator set*: Different subsets of variables were used in the current sensitivity analysis and the impact was high for some scenarios. The construction of the index without the variable "median income" resulted to have a smaller influence on the algorithm construction. Accordingly, we propose to exclude this variable from the corresponding case study.

In summary, it can be concluded that the scenario focusing on the 15 variables without the variable "median income", using the Kaiser criterion for component selection and equal weights for summing the components, is highly recommended for future use. Moreover, the scenario with different weights could also be used but then, additional knowledge on the characteristics of a region is necessary for the interpretation of the results.

The participants of the workshop held on October 27, 2022, at Karlstad University brought up many important aspects linked to both the development and the use of a vulnerability index. The participants discussed the index, the factors and the challenges of weighting these factors from different perspectives, based on their professional backgrounds. Some participants considered this exhausting given that many of the factors are context-specific. For example, household size, population density, and population change were taken up as examples where both low and high figures could be either positive or negative.

The workshop participants also brought up different applications of the index: many of the participants thought a vulnerability index would be a useful tool for planning and communicating different risk management options. They also suggested that if combined with public health data, the index could be used to plan home care and other public health interventions. The use of an index could also generate new information and reveal other risks and opportunities than *"the ones (problems/risks) that we actually handle"*. However, some participants also pointed out that one should be cautious when using an index, since *"the actual conditions change all the time"* and so both the index as well as any measures require regular evaluation.

In risk mitigation and reduction, social vulnerability indices are a potentially powerful tool. They provide quantitative metrics to compare different regions, summarize complexity and they are easy for non-experts to interpret. Those advantages make it likely that they will continue to be attractive to stakeholders, practitioners and decision-makers. Considering the sensitivity analysis in the index construction presented in this study, the SVIS suggested should proceed cautiously and be coupled with expert guidance to ensure that the representation of social vulnerability is reasonable and consistent.

Moreover, as there are also other dimensions of vulnerability, such as physical, economical, institutional etc. (see e.g., Karagiorgos et al., 2016; Papathoma-Köhle et al., 2021). The SVIS may also be combined with such other dimensions in order to provide a comprehensive overview on vulnerability and to identify and understand the main pillars to be used in DRR, and to better understand relationships among social vulnerability models and disaster outcomes (see e.g., Rufat et al., 2019). Additionally, many results of social vulnerability assessments pose the challenge of social and, specifically, distributional justice as those who pay for mitigation and adaptation are regularly not those who are the most affected by a hazard (see the discussion in Thaler et al., 2018). Nevertheless, comprehensive scientific studies on this phenomenon and related policy implications are under-represented so far.

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