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SoResilere—A Social Resilience Index Applied to Portuguese Flood Disaster-Affected Municipalities

Rita Jacinto [1,2,*], Fernando Sebastião [3,4,5], Eusébio Reis [1,2] and João Ferrão [6]

[1] Centre of Geographical Studies, Institute of Geography and Spatial Planning, Universidade de Lisboa, R. Branca Edmée Marques, 1600-276 Lisboa, Portugal
[2] Associated Laboratory Terra, R. Branca Edmée Marques, 1600-276 Lisboa, Portugal
[3] LSRE-LCM—Laboratory of Separation and Reaction Engineering-Laboratory of Catalysis and Materials, Polytechnic of Leiria, 2411-901 Leiria, Portugal
[4] ALiCE—Associate Laboratory in Chemical Engineering, Faculty of Engineering, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal
[5] School of Technology and Management, Polytechnic of Leiria, 2411-901 Leiria, Portugal
[6] Institute of Social Sciences, Universidade de Lisboa (ICS-UL), Av. Prof. Aníbal Bettencourt 9, 1600-189 Lisboa, Portugal
* Correspondence: ritajacinto@edu.ulisboa.pt

Abstract: Decades of academic discussion on social resilience have led to the development of indicators, indexes, and different approaches to assessing it at national and local levels. The need to show real-world applications of such assessments is evident since resilience became a political and disaster risk reduction governance component. This article gives a full description of the methodology used to develop SoResilere, a new social resilience index applied to flood disaster-affected Portuguese municipalities. Study cases were selected according to historical databases, academic sources and governmental entities. Statistical methods for data dimension reduction, such as Factor Analysis (through Principal Component Analysis), were applied to the quantitative data and Optimal Scaling to the categorical data. SoResilere results were analyzed. Since SoResilere is a new tool, component weighting was applied to compare results with no weighting, although it did not affect the SoResilere status in 55.5% of the study cases. There is a tendency to look at the improvement of SoResilere results with component weighting due mainly to the quantitative subindex. There is no evidence of the benefits of component weighting, as no logical association or spatial pattern was found to support SoResilere status improvement in 22.22% of the study cases.

Keywords: social resilience; resilience index; floods; municipalities resilience assessment

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1. Introduction

Floods are responsible for enormous losses in the world, with around '11% of the loss of life occurring from 1998 to 2017'. In a climate change context, the situation is expected to worsen by about 50% [1] in magnitude and frequency of events [2], namely in Portugal [3]. In the Mediterranean and Southern European context, in which Portugal is included, floods have been one of the more destructive phenomena [4,5]. In Portugal, flash floods that occur in the winter are the more fatal ones [4]. In Portugal, there are few studies at a local level scale that focus on flood-related phenomena and their consequences [6].

Disaster resilience is an important feature in the disaster management field [1], and its implementation is of the essence. Disaster resilience was considered an abstract concept by Cutter et al. (2014) [7]. More recently, several studies have referred to disaster resilience and resilience assessment as important support or tool to strengthen decision-making and disaster risk governance [1,8–10]; therefore, it is part of the political agenda worldwide [5,7,11]. There have been several attempts to quantify resilience, namely by employing indicators [3,8,12,13]. Some studies report that an initial resilience assessment contributes to increased resilience, notably by developing and applying indices that assess resilience to disaster or social resilience [1,2,7,9,14,15].

Indexes are useful tools in the disaster risk management field, namely in resilience assessment and in support of decision-making [1,16,17]. Some indexes focus on municipalities or counties, and others focus on the national scale [1,7,15]. Despite its usefulness, indexes are a reductionist picture of a vast and complex reality [15], in this case, of natural and social systems and their interactions. Therefore an indicator-based approach will always have its limitations as the chosen indicators will show more clearly a dimension of social resilience or a phase of disaster recovery, as referred to by Leandro et al. [18] when explaining the limitations of the flood resilience index. In the Social Resilience field, the limitations are also related to the few real-world application with validation, which in the future will show the key indicators for each dimension and phase of social resilience.

Due to the lack of a clear definition of the social or community resilience concept, several studies compare vulnerability with resilience as being equivalent; the same comparison is made between vulnerability and resilience assessments [1,2,7,13,15]. The social resilience concept in the current work is the one described by Jacinto et al. (2020): a set of "positive characteristics (. . .) that promote well-being and recovery, as well as the ability to learn" (Jacinto et al., 2020, p. 3) [5]. Although the current research does not analyze social vulnerability, it is assumed as a set of debilities that turns individuals more prone to harm or suffer damages in a disastrous situation [3,5].

As a contribution to bridging the methodological gaps in social resilience assessment [5], the current research proposes a baseline social resilience assessment of flood disaster-affected Portuguese municipalities—the SoResilere Index, which is a new tool, for the first time presented. The indicators for the index formulation were the ones suggested in Jacinto et al. (2020) article (Jacinto et al., 2020: Appendix 2). Data to meet the indicator requirements for the dimension is (1) Individuals and (2) Society, and both were selected from available official statistics. Data related to the dimensions: (3) Governance, (4) Built Environment, (5) Natural Environment and (6) Disaster were all collected online from available official websites of the local governments and planning instruments, as there were no statistical data to meet the needs for such indicators. This led to two different types of data (quantitative and categorical) that required two different methodologies in the statistical dimension reduction analysis.

SoResilere is the combination of the quantitative and categorical subindexes. The main constriction on building SoResilere was to find and generate the needed data, which was either on different spatial scales or did not exist. There were serious limitations to the selection of the quantitative data for each indicator since there are no statistics regarding psychological preparedness for natural hazards nor consistent data collection regarding disaster risk reduction needs. Moreover, the more suitable indicators were either available at a country-level scale only, or were not periodically collected and, in some cases, there is no certainty that they will be collected again. In both cases, the solution was to exclude the data. Hence the developed methodology can easily be used by local governments.

This paper comprises five sections. Section 2 is a review of social resilience indexes and assessments in the International and Portuguese contexts; Section 3 describes the methodology for data and case study selection, as well as data reduction methods; Section 4 presents the results of the dimension reduction methods; Section 5 discusses data sources accuracy, dimension reduction results and presents SoResilere and spatial distribution analysis. Further findings, main conclusions and next steps can be found in the Section 6 conclusions.

2. State of the Art

2.1. Social Resilience Assessments and Indexes: International Context

Resilience assessment in disaster risk management can be considered an emergent scientific area that requires extensive research to support risk governance (public policy, disaster risk management etc.) [1,8,19,20]. Several resilience assessments have recently been published. The use of indexes to assess disaster resilience is well-established [1,19,21]. The comparison between disaster vulnerability and disaster resilience is still very common [1]. Authors refer to the need for assessment methods that are simple and easy to use by decision-makers [2,20]. In the revision of 174 research articles, Cai et al. (2018) mentioned that 39.1% of the articles used quantitative methods, 39.7% made qualitative assessments, and 10.3% made empirical validation of their assessments [8].

A review of quantitative resilience assessments is presented herein.

Baseline Indicators for Communities (BRIC) is an empirically-based county-level resilience index developed by Cutter et al. (2014) in the United States. The authors grouped the indicators into six domains: social, economic, housing and infrastructure, institutional, community, and environmental. Data were collected from free public data sources. The collected data were transformed and normalized (using the min-max scale, 0 to 1) so that the higher values were the most resilient. Using correlation analysis and conceptual analysis, the initial 61 variables were reduced to 49. Cronbach's Alpha was used to test the internal consistency of the indicators to construct a composite index. BRIC was the sum of the sub-indexed of each domain ranging from zero to 6, with zero denoting the lowest resilience and 6 the highest. The authors applied Principal Component Analysis to the 49 indicators. Through the decomposition of BRIC into its conceptual categories, authors found the main resilience patterns and the drivers. The authors found it difficult to find comparable data for the entire territory of the United States of America and reported the difficulty in finding environmental data [7].

Khalili et al. (2015) developed a framework that coupled social resilience indicators to the disaster phases, namely pre-disaster, response and recovery. Applied in two flood-affected study cases in Australia, in which the data collection was implemented through interviews with experts. State Emergency Service Experts' analysis validated the measures, their weighting and their distribution through the disaster phases.

In South Africa, Kotzee & Reyers (2016) developed a composite social-ecological flood resilience index (FRI). The case studies involved three flood-affected municipalities. The index comprises five components: social, economic, ecologic and structural: the latter relates to institutional resilience. Components were found with Principal Component Analysis (PCA) of 24 indicators. Variables were normalized by applying the min-max formula. Weighting was based on the PCA results; factor loadings and eigenvalue were used to find the ponderation for each indicator. Weighting effects were evaluated. The authors considered that spatial analysis of the results was a useful tool since it provides the geographic location of the resilience, better-informed decision making and the identification of the main drivers of flood resilience [2].

The United States National Hazard Resilience Screening Index (NaHRSI), developed by Summers et al. (2018), characterizes resilience at a county level by evaluating its vulnerability and recoverability. The index covers different types of natural hazards caused by meteorological events. The NaHRSI includes basic resilience (ratio between governance and risk), adaptation and transformation. The index covers the following resilience domains: governance, social attributes, built environment, and natural environment.

Norway Baseline Indicators for Communities (BRIC), a community resilience index, is composed of 47 indicators and 6 subdomains: social resilience, community capital, economic resilience, institutional resilience, infrastructure and housing resilience, and environmental resilience. The Norway application is an adaptation of the original Cutter et al. (2014) BRIC. Two calculations were performed, one with the initial components and with the variables distributed according to those subdomains and another one following the application of Principal Component Analysis (PCA). The Results were similar in both calculations. The authors consider that the index should be compared with different ways to assess resilience to reduce the biases inherent to the construction of the index since it is a simplification of a complex system or reality [15].

Clark-Ginsberg et al. (2020) research is focused on the Analysis of the Resilience of the Communities to Disaster (ARC-D) toolkit, which was developed along a 10-year project by GOAL—an international humanitarian and development organization. The resilience-building toolkit was implemented in Tegucigalpa, Honduras. The toolkit comprises 210 questions raised in focus group discussions. The Questions are correlated with the Sendai Framework priorities and are grouped into 30 components. The resilience values range from 1 to 5, where 1 is minimal resilience, and 5 is full resilience. The authors concluded that through the application of the ARC-D toolkit, the GOAL organization could implement changes and improve resilience in the study case [20].

In Myanmar, flood-prone areas were studied by Lwin et al. (2020) to capture the characteristics of communities with high social resilience. An indicator-based framework comprising different components (social demographic, sense of place, adaptive capacity, flood risk level, and social resilience status of the community) was applied. According to the study, communities located in high flood-prone areas have higher flood risk awareness than those in low flood-prone ones. Field data collection was done by submitting a questionnaire in two phases. A Weighted Average Index (WAI) was calculated to assess social resilience. The results were expressed on a 5-point Likert scale [14].

Parsons et al. (2021) developed the Australian Disaster Resilient Index, a national-scale disaster resilience composite index. The index comprised three dimensions: disaster resilience, coping and adaptive capacity, and three domains, social, economic and institutions and was assigned to the state regions. The index formulation does not include weighting of the indicators, assuming their equal contribution instead. Index mapping was performed using percentiles on all data that had previously been standardized to values between 0–1. Findings point out remoteness as being correlated with less resilience [1].

Rana et al. (2021) analyzed the complexity of flood resilience by assessing community resilience to floods in three communities in Pakistan. Data from 57 indicators were collected by filling out a questionnaire in each of the study cases. The data thus collected was standardized, and an index was formulated. The weighting of indicators was determined by experts using a ranking method [22].

Community resilience assessment in the flood-affected Jamalpur District in Bangladesh was based on a survey applied to 400 households. Besides the survey, another type of data collection was implemented for key stakeholders: Focus Group Discussion, In-depth Interviews and Key informant interviews. The index components are social resilience, economic resilience, institutional resilience, and physical resilience. The Resilience Index ranges from 0 to 1, and the weighting of indicators was based on an expert's analysis. Conclusions stress that to increase social resilience, it is necessary to improve social awareness by raising community participation in hazard programs [9].

The studies reviewed above show that community and social resilience assessments are not always dependent on a specific or exclusive type of hazard or disaster. The analysis of the different disaster phases is not a recurrent method. It is usual to assess resilience at a local geographic scale, although this is not a rule. Local-scale also varies; it can refer to affected places or administrative borders (local governments). This summary of state of art shows that this research field must gather a wider consensus to establish comparable quantitative resilience assessment methods and to provide decision-makers with replicable and easy-to-use methods to assess resilience at a local level, namely at the local government level.

2.2. Resilience Assessments and Indexes: The Portuguese Context

In Portugal, Social Resilience and Resilience assessments related to disaster risk context are still poorly developed. There are no indexes or comparable approaches to the one presented in this study—SoResilere. Nevertheless, there are several analyses on Vulnerability that are relevant [4,6,23].

Despite the lack of comparable social resilience studies, there are resilience studies applied to Portugal that will be mentioned in this study.

Landscape resilience in Madeira island was analyzed by Bonati (2014). The main conclusions show that the physical risk-prone characteristics of the Island, combined with low levels of community perception and participation, increase the risk-prone tendency of the territory, turning it into riskscapes. The concept of riskscapes is taken as—"(. . .) a landscape exposed to possible damages because of the exposure of value to risk, because of place characteristics and because of bad relationships between its society and ecosystem." [24]. The research also suggested several initiatives to promote sustainability and resilience.

Ferrari et al., 2019, included a dimension of urban resilience at the municipal level in the MOVE project that focused on Portugal and Italy. The said dimension was composed of two sub-dimensions, coping capacity and recovery capacity [25]. The focus of the research was territorial resilience and vulnerability assessment at the municipality level. The MOVE project methodology and conceptual frame presented a view of resilience focused on the "lack of Resilience" [25].

Focused on the UNESCO Portuguese Douro winemaking region, Assumma et al. (2022) developed scenarios to promote resilient strategies and planning to face climate change challenges. Scenarios contemplated Social Network Analysis and provided support for the region to achieve Sustainable Development Goals and meet UNESCO requirements [16].

The research of Carvalho et al. (2016) focused on the development of resilience scenarios in the Porto urban area. Aiming to model future urban heat waves and the impact of resilience strategies under different scenarios, the authors considered the impact of urban green areas and cool roofs (green and white) [26].

Beceiro et al. (2022) assessed the impact of a Nature Based Solution on urban resilience by modeling the contribution of an infiltration basin in the Asprela catchment at Porto city. Their findings point to a positive contribution of the infiltration basin to urban resilience and that this nature-based solution will return good hydraulic conditions even under severe rainfall conditions [17].

Taking into account the organizational, spatial, functional and physical resilience dimensions in the Portuguese capital city of Lisbon, a resilience–assessment framework was applied to the waste and mobility sectors accounting for the UNDRR Disaster Resilience Scorecard for cities and the Sendai Framework for Disaster Risk Reduction. The research of Cardoso et al. (2022) identified the main opportunities to improve the resilience of the waste and mobility sectors in Lisbon, to face climate change and the Disaster Risk Reduction challenges it can bring to these sectors [27].

2.3. Flood-Related Indexes: The Portuguese Context

There are few studies in Portugal dedicated to flood-affected areas, especially regarding the social aspects of floods. Santos et al. (2020) mentioned that there are few flood-related studies at the municipal level in Portugal. Due to the scarce quantitative assessments of floods in Portugal and especially of their social aspects, we provide a short synthesis of recent assessments and their scale of analysis.

Two studies have developed flood susceptibility indices, namely Jacinto et al. (2015) and Santos et al. (2019). The said research works focused mainly on fluvial floods [3,28]. Jacinto et al. (2015a) susceptibility index designed for the study area of mainland Portugal was based on soil permeability, runoff and accumulation. Using flow accumulation, slope and permeability, Santos et al. (2019) assessed flood susceptibility in mainland Portugal. Regarding flood "social susceptibility", which appears to be a new expression for the concept of vulnerability, Grosso et al. (2015) developed an index to identify the populations that are ill-prepared to face flood events [29]. The flood Risk Index was applied by Santos et al. (2020) to understand the flood risk drivers at the municipal level in mainland Portugal.

Few studies in Portugal address quantitatively the concept of Vulnerability; nevertheless, it is worth noting the country-level research by Tavares et al. (2018) that compares the changes in social vulnerability of 278 municipalities in mainland Portugal from 2008 to 2017. We further note a regional Vulnerability assessment of the Greater Lisbon area, in which

Guillard-Gonçalves et al. (2015) applied and adapted Cutter's Social Vulnerability Index (SoVI) [21] to the Portuguese case (Guillard-Gonçąlves, Cutter, Emrh, & Zêzere, 2015).

Having made a brief review of the current state of flood-related indexes, social aspects of floods and resilience research in Portugal, two considerations seem reasonable: (i) resilience research is still incipient in Portugal, therefore, poorly developed; and (ii) the current study on social resilience assessment in flood disaster-affected municipalities is a pioneer study.

Although community and social resilience assessments are becoming more frequent in the scientific community, there is still much to research. There is still a shortage of data to cover some of the dimensions which are usually included, and it is also unclear whether all of the indexes should address the phases of disaster.

3. Materials and Methods

3.1. Case Study Selection

The current research presents a full methodology applied to create an index to assess social resilience in Portuguese flood disaster-affected communities. The criteria for selecting the municipalities, which are at the base of the concept of flood disaster-affected communities, are described in this section. The chosen criteria were the consequences of floods, and the first approach of selection was to choose all the flood-affected municipalities from the project Disaster database (http://riskam.ul.pt/disaster/, accessed on 1 May 2018). As this turned out to be a very broad approach, more specific criteria were established in the sense that the case studies needed to have a history of flood disasters to be selected. The definition of the disaster was the one proposed by the Centre for Research on the Epidemiology of Disasters (CRED), as stated by Bakkour et al. (2015): "(. . .) an event qualifies as a disaster if at least one of the following criteria is fulfilled: 10 or more fatalities are reported; 100 or more people are reported affected, injured, and/or homeless; the government declares a state of emergency, or the government requests international assistance." [30].

Case study selection from municipalities in mainland Portugal was mainly based on the scientific project Disaster historical database for Portugal (http://riskam.ul.pt/disaster/, accessed on 1 May 2018), and only flood events were selected from the Disaster Database. Hence, the Disaster database does not cover the whole Portuguese territory as other historical sources were used in the islands; a regional government Law Decree from Azores Regional Government [31] and an MSc Thesis for Madeira [32] was used to collect historical data for the selection of municipalities in these archipelagos.

Another criterion for case study selection was the possibility of collecting data through municipal plans. Some municipalities were excluded from selection (Figure 1) if their Municipal Emergency Plans, which are the base and support for the civil protection action, were: (i) not available both on the local government website and on the national civil protection Authority website—http://planos.prociv.pt/Pages/homepage.aspx, accessed on 1 May 2021 (Alpiarça Municipality); (ii) the plan was under revision, but its final version was unavailable (Funchal and Golegã Municipalities); (iii) The municipal emergency and civil protection plan available online dates from 1999 (Chamusca Municipality); (iv) In the case of the Municipality of Cartaxo the municipal emergency and civil protection plan available online had only 9 pages (the document was incomplete and not comparable with the others). The data collection, based on Municipal Emergency Plans and other information available online, took place during the period 8 February and 2 June 2021. Figure 1 shows the location of the final set of Municipalities taken as a case study for the SoResilere—Social Resilience Index in Portuguese flood disaster affected Communities Assessment.

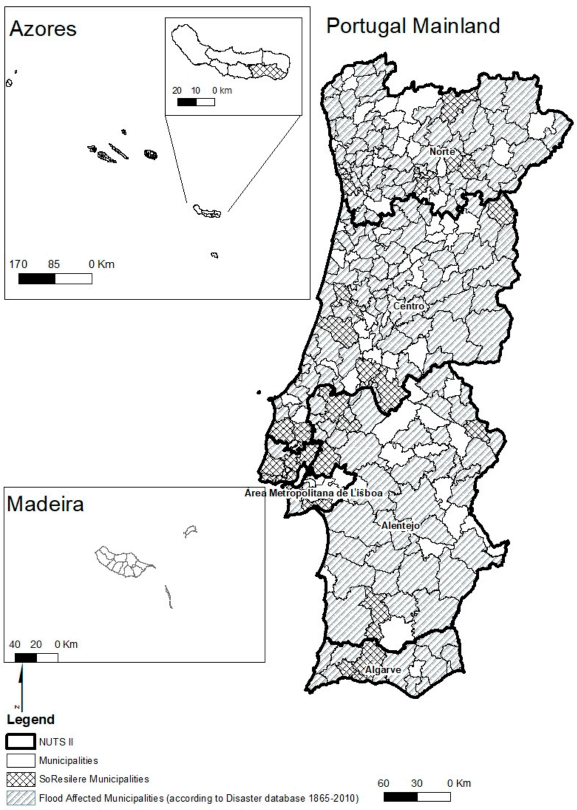

Figure 1. Municipalities selected for SoResilere—authors elaboration (Data sources: CAOP—https://snig.dgterritorio.gov.pt/rndg/srv/por/catalog.search#/home, accessed on 1 February 2020; Disaster—http://riskam.ul.pt/disaster/, accessed on 1 May 2018).

3.2. Data Collection—Sources and Data Required versus Data Available

The required data were defined in agreement with Annex 2 of Jacinto et al. (2020) and presented as an excerpt in Appendix A (August 2022) of this Article. The major difficulty in transposing Jacinto et al. (2020) framework into a real-world assessment in Portugal was the lack of comparable data available in open and free internet-based sources. Data constraints for resilience assessment are not exclusive to this research; Ferrari et al. (2019) and Parsons et al. (2021) referred to the challenges posed by the lack of available data [1,25], and several studies collected/created their data [9,14,22,33,34]. Boylan & Lawrence (2020) pointed out that there is no way to evaluate psychological preparedness in a natural hazard setting; Usually, this data is not public but kept instead for medical purposes; therefore, it is either unavailable, or it does not exist at all [35]. Cutter et al. (2014) used free and open data sources to collect data for the formulation of an empirically-based resilience metric called the Baseline Resilience Indicators for Communities (BRIC) [7].

Given the lack of comparable data with the studies identified by Jacinto et al. (2020), only Dimensions (1) Individuals and (2) Society were collected from statistical sources (see Appendix B). Considering the spatial repercussions of floods in Portugal, which are, in some cases, narrow areas near the rivers [6], the ideal spatial scale would be street or neighborhood or parish level. Having not found any data in such spatial scales among the available statistics, the municipality level was the preferred one, although District and Nomenclature of Territorial Units for Statistics II (NUTS II) were also considered when there were no other options. However, its inclusion was avoided because it might bias the results. Some proxy data were not included due to spatial and temporal scales (see Appendix A). The quantitative data for Dimensions (1) and (2) were collected for all flood-affected municipalities in mainland Portugal and not specifically for the final set of study cases. The aim of using this methodology was to test/compare results of variable reduction by Factor Analysis; hence a larger number of variables would lend robustness to the statistical analysis. The terms variables and indicators are used as equivalent in the current study. Statistics Portugal (INE) was the main data source accessed through two online search engines: INE's official website (https://ine.pt/, accessed on 1 February 2019 to May 2021) and also the Contemporary Portugal Data Base—Pordata (https://www.pordata.pt, accessed on 1 February 2019). For more details see Appendix B.

Unlike in other countries, regional governance and emergency-related data sets do not exist in Portugal. For instance, in Australia, regional governments, and their emergency service agencies or local governments produce data sets related to their regions [1]. The inexistence of data required a different strategy. Therefore Dimensions (3) Governance, (4) Built Environment, (5) Natural Environment, and (6) Disaster data were collected through document reviewing. These comprised Municipal Emergency Plans, Flood Special Plans, Municipal Director Plans, and other relevant documents available online on the local governments' websites and national civil protection authorities' websites. This was the solution found to collect the data in the context of the COVID-19 pandemic and lockdowns. Initially, the plan was to submit a questionnaire and perform interviews with the selected local governments and flood-affected areas of the selected municipalities. Not being able to apply the planned methodology and content analysis on different online available documents allowed the collection of categorical data. Summers et al. (2018) also used online available data [19].

Categorical data collection was based on resilience conditions, herein referred to as categories: resilient (classified with 1) to non-resilient (classified with 0). Whenever possible, a Likert scale with five categories (values 0; 0.25; 0.5; 0.75 and 1) was used to measure resilience levels (0–1, 1 being the most resilient level). Such values are meant to be representative of a percentage of the most resilient categories encountered in the case studies. Whenever it was not possible to establish a five-categories scale, a binary categories scale was used of 0—not resilient, 1—resilient. The set categories were adjusted to the study cases, as other categories to evaluate ideal situations would not be realistic. Given the unavailability of current standard scales for resilience categories in the international bibliography, this methodology was seen as a faithful picture of the current situation for the group of municipalities under analysis. Ideally, a standard data collection based on international scientific agreed categories would lead to a more replicable scale of analysis independent of the case study. Appendix C Metadata for the Categorical Data shows the scale of evaluation for each indicator of the categorical data.

The pandemic context and its impact on this research have had their high and low points. The methodology is focused on the reality under analysis as a picture of the current situation; one weakness is the fact that it does not account for historical processes and projects. The initial methodology would have avoided this weak point as it would account for local government staff's historical knowledge. Conversely, there is a strength in this methodology in the sense that it places the individuals as the central point of social resilience, following the conceptual base of the current research presented in Figure 2 of Jacinto et al. (2020). The collection of data for Dimensions (3) to (6) from online sources promotes awareness about the information available to citizens. An important part of the literature on disaster risk management and governance is the enrolment and the exchange of information with the population in flood-prone areas [14] as part of the population's coping capacity [36]. Therefore, collected data provides a realistic picture of social resilience, risk management and governance accessible to the population. Access to this information forms the basis for public participation and disaster prevention. Regardless of the limitations of this method, we consider it a valid starting point as it offers an interesting individual-focused perspective.

3.3. Reducing the Number of Indicators

The initial set proposed by Jacinto et al. (2020) was drastically reduced by data constraints, namely the spatial scale. The criteria of Parsons et al. (2016) were also taken into account for variable selection and reduction: "The indicator is relevant to the scale(s) of assessment", "The indicator is achievable—data are available, accessible and cost-effective" [36].

Following the application of the criteria, 27 indicators remained for Dimensions 1 and 2 (see Appendix B database of indicators), of which 24 were at a municipal level, 2 at the NUTS II level and 1 at the District level. This data was collected for all the flood-affected municipalities. Principal Component Analysis, a recurrent statistical method in this study area, was used to reduce the number of quantitative indicators in the formulation of indices in different disaster risk components, such as resilience and vulnerability [1,2,7,15,21,23,37]. Data collection for Dimensions 3 to 6 (see Appendix C) resulted in 12 indicators: 9 Likert scales and 3 binary scales. These categorical indicators were collected only for the municipalities in which the above-mentioned criteria of flood disaster history were verified. Optimal Scaling, a procedure of the Categorical Principal Component Analysis (CATPCA) statistical technique, was used to reduce the dimensionality of the categorical data.

Both Principal Component Analysis and CATPCA through Optimal Scaling were used to reduce the number of variables, reorganize the indicators into components and understand which ones were statistically more relevant.

3.4. Data Analysis

Inspired by Cutter et al. (2003) methodology to generate SOVI and Lwin et al. (2020a) methodology to assess social resilience in flood-affected communities that applied data dimension reduction methods, PCA and CATPCA through Optimal Scaling were applied to quantitative data (Dimensions 1 and 2 Appendix B) and categorical data (Dimensions 3 to 6 Appendix C), respectively.

Descriptive statistics analysis was applied to both sets of variables. Regarding the quantitative data, the standardized values were saved as variables, and the Z-scores used for Factor Analysis. The standardized data (Z-scores) were used for Factor Analysis as per Cutter et al. (2013). The application of Factor Analysis followed Marôco (2021) publication.

Principal Component Analysis (PCA) was applied to the quantitative data set in the following variation of its composition: (i) 27 variables and 255 municipalities; (ii) 24 variables (excluding indicators at NUTS II and district level) and 255 municipalities; (iii) the 27 variables of Dimension 1 and Dimension 2 were divided into separate files/analysis, and the 255 floods affected municipalities; (iv) 24 variables (excluding indicators at NUTS II and district level) were separated into Dimension 1 and Dimension 2, and the 255 floods affected municipalities. The same variations of the composition of datasets (i) to (iv) were tested for the 255 flood-affected municipalities and the 36 flood-disaster-affected municipalities. Although the balance between 36 flood disaster-affected municipalities and 27 variables can be argued, it still respects the fact that the number of cases should be bigger than that of the variables in a PCA methodology. The balance between the case study and variables was the reason for the collection of statistics-based indicators in the 255 flood-affected municipalities because a substantially larger sample than the number of indicators ensures greater robustness of the PCA. The analysis was done, first without rotation of the components and then with Varimax rotation. Kaiser-Meyer-Olkin (KMO) test was used to evaluate sample adequacy [38], which was also applied by Tavares et al. (2018).

Optimal Scaling through CATPCA was applied to the categorical data that were collected only for the 36 case studies that involved municipalities affected by flood disasters. When employing Optimal Scaling the user must establish the number of components that will be analyzed. Following the suggestion of Marôco (2021), other analyses were then made with a focus on the percentage of variables explained by each component. To decide how many components should be retained, the following criteria were applied: the eigenvalue should be superior to 1, as an eigenvalue inferior to 1 shows scores that are explaining less than the original variable [38,39]. The analysis of Cronbach's Alpha was also taken into account as it gives feedback on the reliability of the model; the higher the Cronbach's

Alpha value the higher the reliability of the model. A negative Cronbach's Alpha shows that the component is not reliable [38].

4. Results

4.1. Results for PCA of the Quantitative Data

Results from Factor Analysis for the quantitative data in the various analyzed conditions are presented in Table 1. Further details related to the results not shown in the text can be consulted in Appendix D Total Variance Explained and Component Matrix from conditions: (i), (ii) and (vii), namely in Tables A1–A6.

Table 1. Factor Analysis Results for the quantitative data (Dimensions 1 and 2—Appendix B).

Condition	KMO	KMO Classification According to [38]	Explained Variance (Cumulative %—Extraction of Squared Loadings)
27 Variables and 255 municipalities.	0.774	Average	Seven factors explain 69.672% of the variance (with an eigenvalue higher than 1). From those, the first six explain 65.771% of the variance. Validating with the scree plot, only the first 6 factors should be considered since there's a clear change in the inflexion of the scree plot (see Figure 2) and also the eigenvalue of the 6th factor is above 1 (1.417—see Table A4), the 7th was excluded as the eigenvalue is very close to 1 (1.053—see Table A4).
(ii) 24 variables (excluding NUTS II and District level indicators) and 255 municipalities.	0.779	Average	Six factors explain 67.197% of the variance (with eigenvalue higher than 1). Checking with the scree plot, the 6 factors should be considered since there's a clear change in the inflexion of the curve in the scree plot (see Figure 3) and also the eigenvalue of the 6th factor is clearly above 1 (1.127—see Table A6).
19 variables (Dimension 1, 19 from the 27 variables), and 255 municipalities.	0.719	Average	Six factors explain 72.550% (Cumulative) of the variance. Confirming with the scree plot, only the 5 factors should be considered since there's a clear change in the inflexion of the curve in the scree plot (see Figure 4).
10 variables (Dimension 2, 10 from the 27 variables), and 255 municipalities. Note that 2 of the original indicators are the same for Dimensions 1 and 2, therefore there are 8 variables in Dimension 2.	0.683	Poor	Three factors explain 58.891% of the variance. Confirming with the scree plot, if this Factor Analysis is used, the 3 factors have eigenvalues above 1 (see Figure 5), nevertheless they explain less than 60% of the total variance which would not be suitable [23].
17 Variables Dimension 1 (excluding indicators at NUTS II), 255 municipalities.	0.716	Average	Five factors explain 67.881% of the variance. Confirming with the scree plot, all the 5 factors should be considered since all have eigenvalues higher than 1 (see Figure 6).
9 Variables Dimension 2 (excluding indicators at the District level), 255 municipalities.	0.731	Average	Three factors explain the 60.934% of the variance. Confirming with the scree plot the three factors must be considered (see Figure 7).
27 Variables, 255 municipalities with Varimax Rotation.	Same as condition (i) (the entry data is the same, the only change is the output Varimax Rotated Matrix).		
24 Variables (excluding NUTS II and District level variables) 255 municipalities with Varimax Rotation.	Same as condition (ii) (the entry data is the same, the only change is the output Varimax Rotated Matrix).		
27 Variables, 36 municipalities.	0.539	Poor	Six factors explain 78.890% of the variance. From those, the first five explain 73.468% of the variance. Confirming with the scree plot, only the first 6 factors should be considered since there is a clear change in the inflexion of the curve in the scree plot (see Figure 8).
24 Variables (excluding NUTS II and District level variables) 36 municipalities.	0.628	Average	Six factors explain 80.081% of the variance. From those, the first five explain 73.985% of the variance. Confirming with the Scree Plot, only the first 6 factors should be considered since there's a clear change in the inflexion of the curve in the scree plot (see Figure 9).

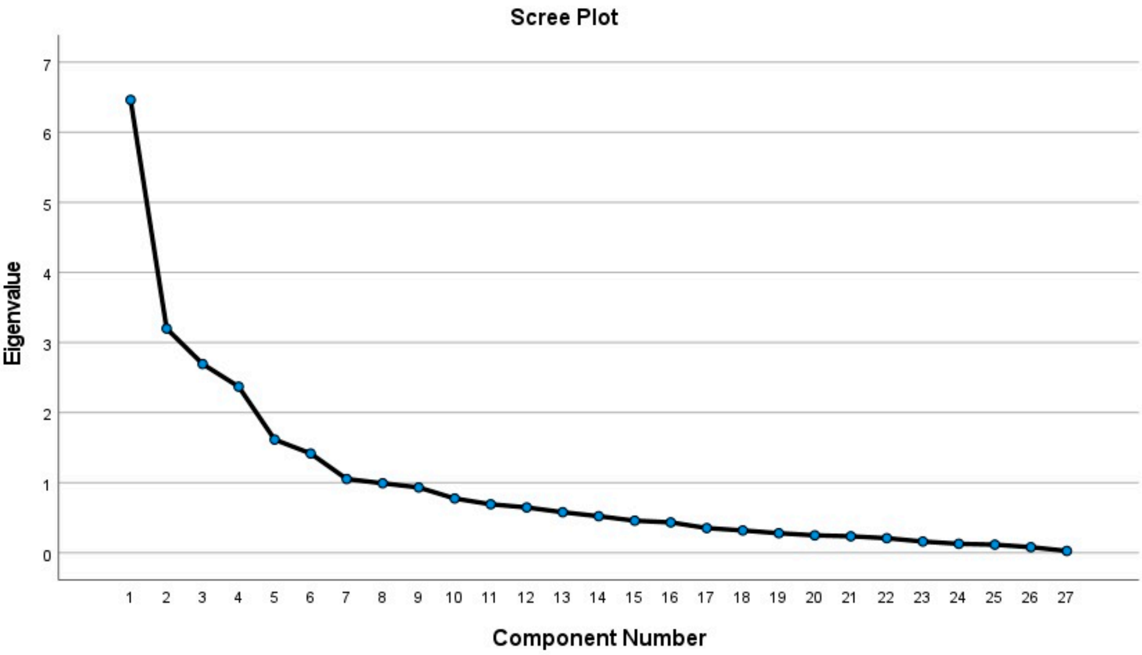

Figure 2. Scree Plot from Factor Analysis for 27 variables and 255 flood-affected municipalities.

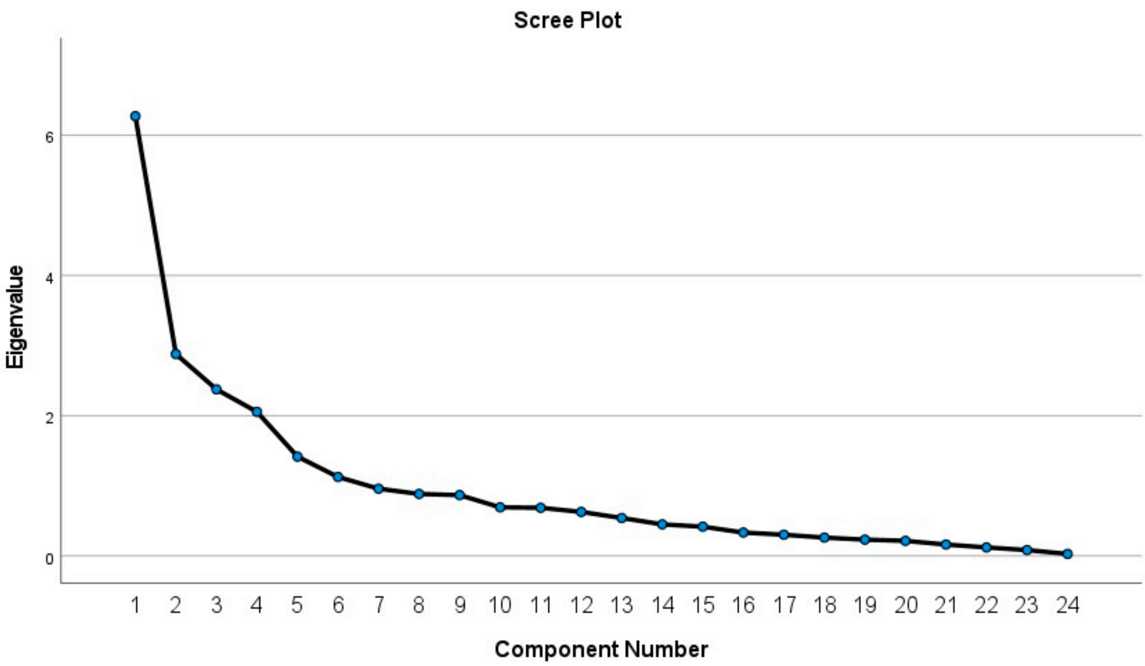

Figure 3. Scree Plot from Factor Analysis for 24 variables and 255 flood-affected municipalities.

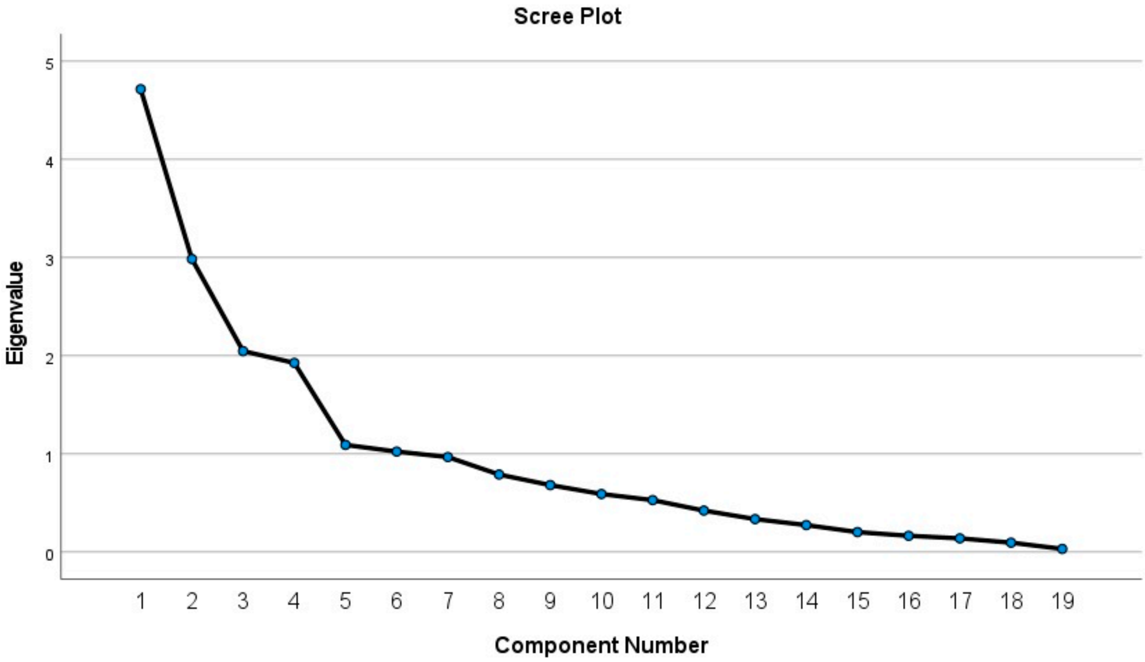

Figure 4. Scree Plot from Factor Analysis for Dimension 1 (19 variables) and 255 flood-affected municipalities.

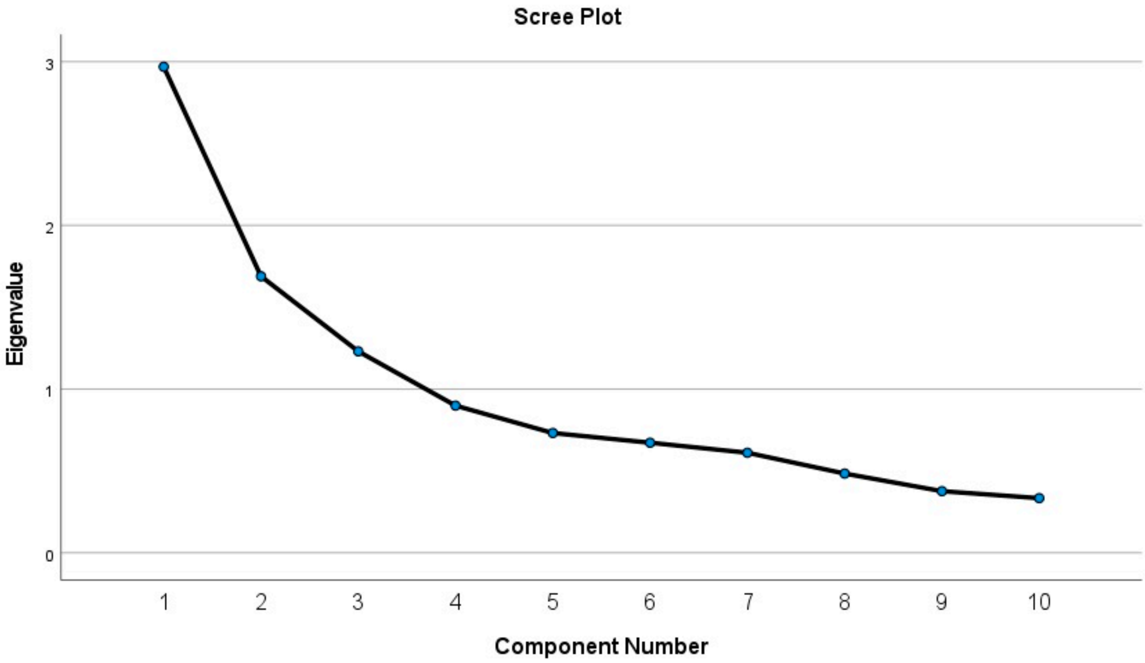

Figure 5. Scree Plot from Factor Analysis for Dimension 2 (10 variables) and 255 flood-affected municipalities.

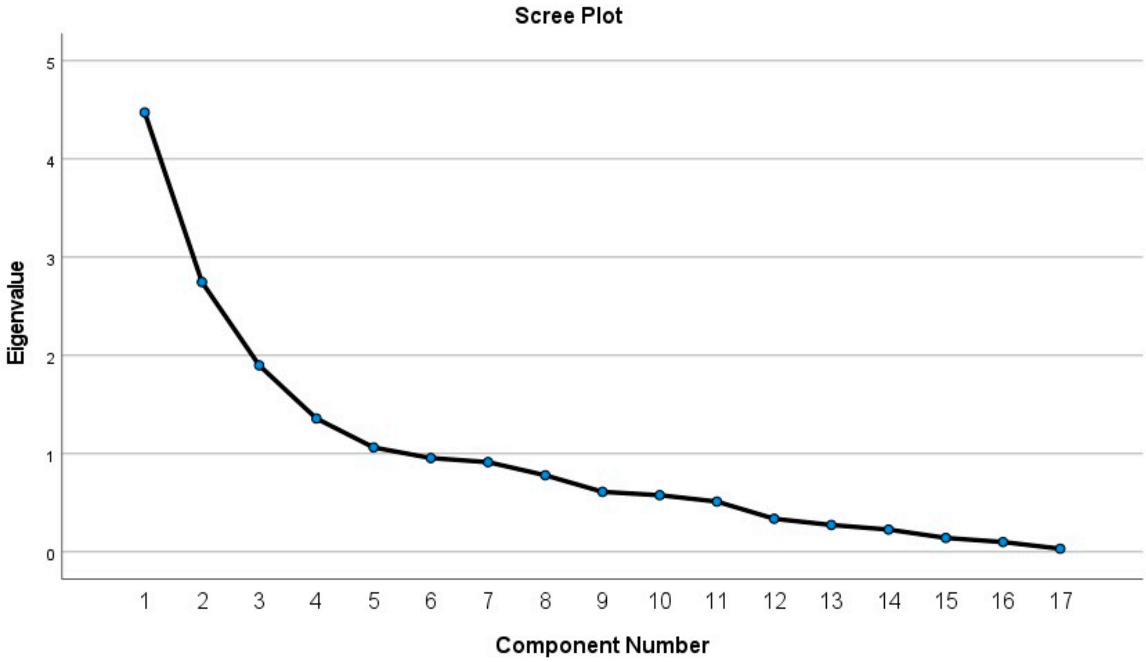

Figure 6. Scree Plot from Factor Analysis for Dimension 1 (17 variables—only municipal level) and 255 flood-affected municipalities.

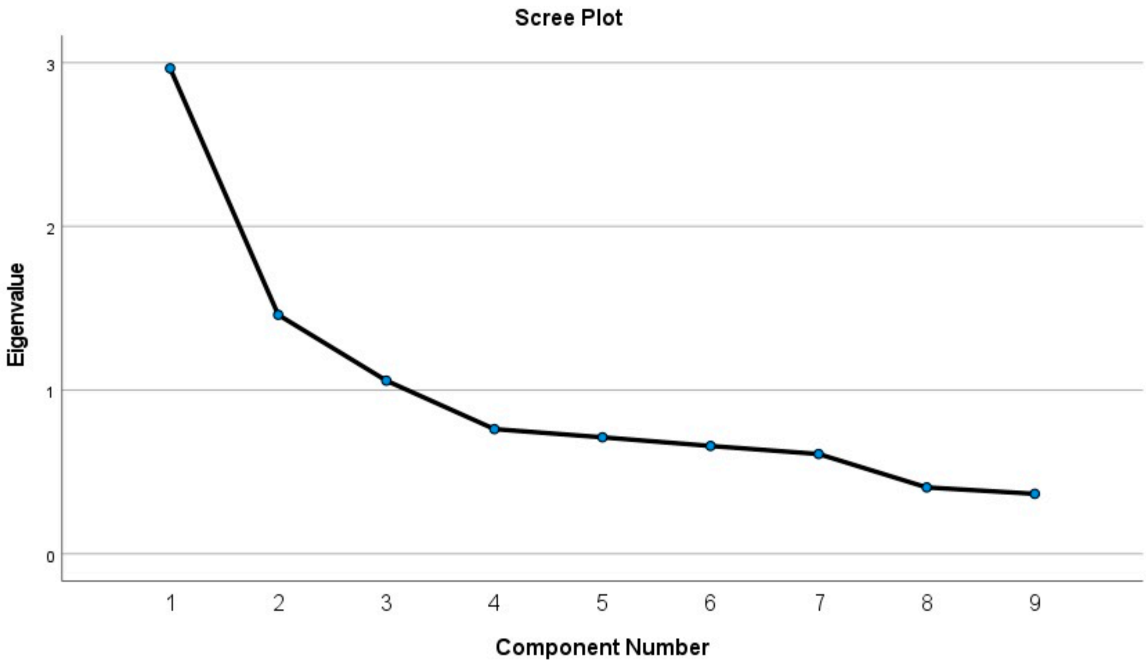

Figure 7. Scree Plot from Factor Analysis for Dimension 2 (9 variables—only municipal level) and 255 flood-affected municipalities.

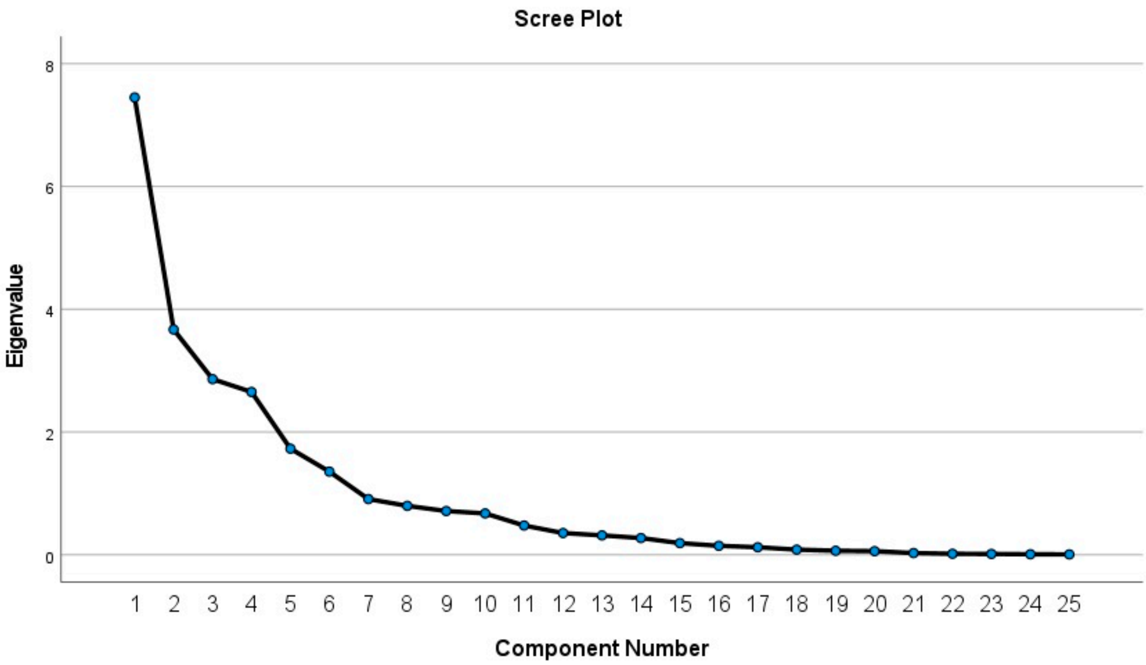

Figure 8. Scree Plot from Factor Analysis for 27 variables and 36 municipalities.

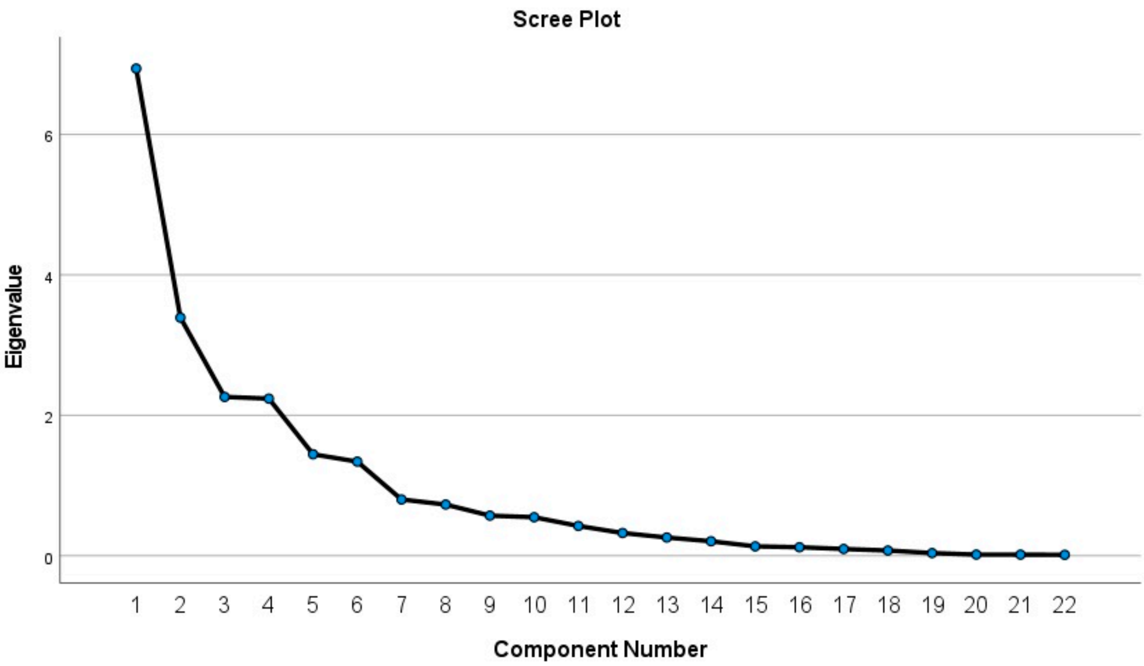

Figure 9. Scree Plot from Factor Analysis of 24 variables and 36 municipalities.

Table 2 shows the total variance explained for condition (viii), and Table 3 shows the Rotated Component Matrix in which the loadings of the standardized variables are also shown. The values in the module of each variable are highlighted, allowing us to group the component variables in which the loadings were higher. Loadings under 0.5 in the module show that the variables should be excluded [23].

Table 2. Total Variance Explained condition (viii) 24 variables and 255 municipalities with Varimax Rotation.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.273	26.137	26.137	6.273	26.137	26.137	3.848	16.033	16.033
2	2.880	11.999	38.136	2.880	11.999	38.136	3.129	13.039	29.072
3	2.376	9.901	48.037	2.376	9.901	48.037	2.709	11.288	40.360
4	2.055	8.563	56.600	2.055	8.563	56.600	2.678	11.159	51.519
5	1.417	5.902	62.503	1.417	5.902	62.503	2.107	8.781	60.299
6	1.127	4.694	67.197	1.127	4.694	67.197	1.655	6.897	67.197
7	0.959	3.997	71.194						
8	0.884	3.685	74.879						
9	0.868	3.616	78.495						
Extraction Method: Principal Component Analysis.									

Table 3. Rotated Component Matrix from Factor Analysis condition (viii) Twenty-four variables and 255 municipalities with Varimax Rotation.

Rotated Component Matrix [a]						
	Component					
	1	2	3	4	5	6
Z-score(V112) (−)	0.097	0.400	0.053	0.720	−0.142	0.083
Z-score(V113) (−)	−0.127	0.265	0.073	0.037	−0.036	0.657
Z-score(V117)	0.204	−0.269	−0.358	−0.164	0.020	0.584
Z-score(V1181)	0.413	0.642	0.222	0.472	0.097	−0.070
Z-score(V1182)	−0.041	−0.143	−0.329	0.572	0.007	−0.073
Z-score(V1191)	−0.584	−0.433	−0.055	−0.174	0.018	0.309
Z-score(V1192)	0.786	0.282	0.187	0.330	0.015	−0.116
Z-score(V1211)	0.143	0.184	0.129	0.789	0.042	0.137
Z-score(V1311) (−)	0.021	−0.148	−0.775	0.164	0.155	0.079
Z-score(V1312) (−)	0.139	−0.104	0.266	−0.288	0.182	−0.532
Z-score(V1313)	−0.241	0.338	0.722	−0.086	−0.088	−0.096
Z-score(V1321)	0.090	0.568	0.211	0.410	0.319	−0.326
Z-score(V1322)	−0.187	−0.125	−0.119	−0.051	0.869	0.032
Z-score(V1331)	0.472	−0.018	0.379	0.249	0.280	0.327
Z-score(V1411)	−0.915	0.012	0.213	0.070	0.096	0.004
Z-score(V1423) (−)	0.889	0.132	−0.212	0.068	−0.097	0.054
Z-score(V143) (−)	0.012	−0.207	0.615	0.298	−0.135	−0.030
Z-score(V212) (−)	0.075	0.658	0.207	0.268	−0.204	0.070
Z-score(V221) (−)	0.317	0.621	0.139	0.151	0.014	0.205
Z-score(V222) (−)	0.004	−0.006	0.134	0.043	−0.866	0.180
Z-score(V2232)	0.045	0.784	−0.070	−0.092	−0.093	0.066
Z-score(V2413) (−)	0.617	0.078	0.379	−0.116	−0.385	−0.225
Z-score(V2414)	−0.352	−0.290	−0.387	−0.480	0.292	0.152
Z-score(V2415) (−)	0.214	0.154	0.343	0.150	0.049	−0.254
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [a] [a]. Rotation converged in 15 iterations.						

4.2. Results from the Optimal Scaling (CATPCA)

Optimal Scaling was the dimension reduction methodology applied to the categorical data collected for the 36 flood disaster-affected municipalities. Results are shown in Table 4.

Table 4. Categorical Data Optimal Scaling (CATPCA) Model Summary Results.

Condition (a) CATPCA 36 Municipalities, 12 variables, 12 Dimensions in Solution			
Model Summary			
Dim	**Cronbach's Alpha**	**Variance Accounted For**	
		Total (Eigenvalue)	**% of Variance**
1	0.639	2.413	20.107
2	0.622	2.329	19.405
3	0.326	1.427	11.891
4	0.214	1.245	10.373
5	0.093	1.094	9.114
6	−0.037	0.967	8.060
7	−0.412	0.726	6.047
8	−0.681	0.616	5.132
9	−1.015	0.518	4.317
10	−2.296	0.322	2.684
11	−4.280	0.203	1.693
12	−6.623	0.141	1.178
Total	1.000 a	12.000	100.000
a. Total Cronbach's Alpha is based on the total Eigenvalue.			
Condition (b) CATPCA 36 Municipalities, 12 variables, 5 Dimensions in Solution			
Model Summary			
Dim	**Cronbach's Alpha**	**Variance Accounted For**	
		Total (Eigenvalue)	**% of Variance**
1	0.751	3.214	26.787
2	0.649	2.466	20.548
3	0.330	1.434	11.953
4	0.239	1.281	10.677
5	0.082	1.081	9.010
Total	0.976 a	9.477	78.975
a. Total Cronbach's Alpha is based on the total Eigenvalue.			
Condition (c) CATPCA 36 Municipalities, 12 variables, 5 Dimensions in Solution with Varimax			
Model Summary Rotation			
Dim	**Cronbach's Alpha**	**Variance Accounted For**	
		Total (Eigenvalue)	**% of Variance**
1	0.726	2.801	23.340
2	0.627	2.117	17.640
3	0.569	1.900	15.832
4	0.422	1.355	11.288
5	0.273	1.305	10.876
Total	0.976 b	9.477	78.975
Rotation Method: Varimax with Kaiser Normalization. b. Total Cronbach's Alpha is based on the total Eigenvalue.			

Table 5 shows the component loadings of each variable per dimension for conditions (b) and (c). Loadings are highlighted to show which variables will be considered in each of the dimensions/components.

Table 5. Categorical Data Optimal Scaling (CATPCA) Component Loadings and Rotated Component Loading Results.

Condition (b)					
Component Loadings					
	Dimension				
	1	**2**	**3**	**4**	**5**
V311	0.544	0.236	−0.093	−0.438	−0.304
V3112	−0.146	0.853	0.040	0.048	0.276
V3117	0.917	−0.052	0.317	−0.025	0.098
V3151	0.588	0.588	−0.116	−0.025	−0.346
V3152	−0.352	0.437	0.620	0.065	−0.213
V4121	0.901	−0.119	0.320	−0.042	0.038
V511	0.343	0.041	−0.523	0.479	0.097
V6112	−0.169	0.617	0.442	−0.148	0.177
V3141	−0.005	0.104	0.294	0.853	−0.014
V3113bi	0.191	0.741	−0.426	0.179	−0.296
V3114bi	0.437	0.273	−0.142	−0.082	0.771
V313bi	−0.633	0.335	−0.258	−0.252	0.117
Variable Principal Normalization.					
Condition (c)					
Rotated Component Loadings [a]					
	Dimension				
	1	**2**	**3**	**4**	**5**
V311	0.390	0.484	0.007	−0.036	−0.507
V3112	−0.288	0.430	0.556	0.484	0.135
V3117	0.943	0.112	−0.030	0.221	−0.048
V3151	0.356	0.823	0.102	0.041	−0.098
V3152	−0.091	0.040	0.794	−0.250	0.212
V4121	0.946	0.081	−0.059	0.142	−0.071
V511	0.049	0.368	−0.549	0.261	0.351
V6112	−0.073	0.113	0.762	0.242	−0.002
V3141	0.123	0.050	0.115	−0.067	0.888
V3113bi	−0.159	0.918	0.025	0.097	0.096
V3114bi	0.219	0.064	−0.041	0.911	−0.068
V313bi	−0.741	0.045	0.218	0.128	−0.205
Variable Principal Normalization.					

[a]. Rotation Method: Varimax with Kaiser Normalization. Rotation failed to converge in 6 iterations. (Convergence = 0.000).

4.3. Social Resilience Index—SoResilere

4.3.1. SoResilere Index Calculation—Part 1: The Quantitative Data

For quantitative data results, please see Table 3—Rotated Component Matrix from Factor Analysis condition (viii) 24 variables and 255 municipalities with Varimax Rotation that shows the distribution of indicators whose values are above 0.5 in module per component. Components were classified according to the variable with a higher score in the module; the definition of Dimensions and Components was based on Jacinto et al. (2020)—Appendix A of this paper. Components 1 and 2 explain 29.072% of the total variance, and 67.197% of the total variance is explained by the 6 components. The variable with the highest score in a module or, when very approximate scores, the two variables with the highest scores in the module, are now presented as those variables were selected to assume the main contribution to describe each component of factor and also to label the components.

Component 1 is related to the resilience dimension of Individuals and Component Migration. The highest scores in the module belonged to variables V1411 and V1423, both originated from the same quantitative indicator: Foreign population with the legal status of residence (No.) by Place of residence (NUTS-2013), Sex and Nationality (Groups of countries). Nevertheless, V1411 which had the highest score in the module, is a proxy for language proficiency and the variable V1423, which relates to the connection of individuals to the place of residence, registered the highest value. The two variables with the highest scores are related to Migration.

Component 2 relates to the dimension of Society and the component of Social Networking. V2232 is a proxy for women empowerment; calculations of the percentage of women that work in local governments were made based on the indicator Employees in Local Government.

Component 3 concerns the dimension of Individuals and the component Age and Demography. The variables V1311 and V1313 scored the highest in the module and are both related to the characteristics of the resident population, Age (% of the population under 15 and above 65 years of age) and marital status (% of married) respectively.

Component 4 relates to the dimension of Individuals and the component of Health and Disability. The variable with the highest score in the module is V1211—Specialist medical doctors. The variable with the second highest score in the module is V112—a population with at least one disability.

Component 5 relates to the dimension Individuals and component Age and Demography and indicator Household. The variable with the highest score, V1322, is associated with private households. Although this component only contains two variables, both got high scores. The variable V222 is related to Unemployment registered at the public employment office and includes the total percentage of the resident population aged 15 to 64 years. Given the economic context, the combination of these two variables, both with scores higher than 0.86, makes this component an Economic or financial status of individuals.

Component 6 relates to Individuals, Psychology/Adaptive Capacity and indicator capacity to deal with changes, stress and self-control and regulation. Variable V113 is associated with deaths according to the death cause, namely self-inflicted death.

This section is presented the formula applied to the quantitative data set, therefore, the quantitative data subindex. Component variance explained rates were applied to the subindex calculation (Equation (1)). The weights of the components decrease from components 1 to 6—(Table 3). The use of the PCA results on index components weighting was also applied by Kotzee & Reyers (2016). The variables had positive or negative contributions to the index, as some increased social resilience and others decreased it (see Appendix B). The application of the positive and negative ponderation of indicators according to their contribution to resilience or other disaster risk components, such as vulnerability, is often used in the formulation of indices by different authors [1,7,37].

Equation (1)—Component weighting—quantitative data subindex

$$\begin{aligned}\text{SoResilere} = {} & \left(\frac{-V_{1191} + V_{1192} - V_{1411} + V_{1423} + V_{2413}}{5}\right) * CP_1 + \left(\frac{V_{1181} + V_{1321} + V_{212} + V_{221} + V_{2232}}{5}\right) * CP_2 \\ & + \left(\frac{-V_{1311} + V_{1313} + V_{143}}{3}\right) * CP_3 + \left(\frac{V_{112} + V_{1182} + V_{1211}}{3}\right) * CP_4 + \left(\frac{V_{1322} - V_{222}}{2}\right) * CP_5 \\ & + \left(\frac{V_{113} + V_{117} - V_{1312}}{3}\right) * CP_6\end{aligned} \tag{1}$$

where:

V_x are the variables according to Appendix B;

CP_i is $\frac{Factor\ x\ \%variance}{Total\%\ cumulative\ variance}$, the weighting factor of each component for i = 1, 2, . . . 6.

As referred to in the State of the art (Section 2.1) several international indexes do use component weighting in their indexes, the same was done for SoResilire quantitative subindex as described in Equation (1). Other indices that assess the social aspects of risks, such as SOVI [21] and SOVI application in Portugal [37], in which component weighting was not applied in the calculation of the index, hence the authors considered that there is no robust justification for making such ponderation. Taking into account the two views of component weighting, SoResilere quantitative data subindex calculation was done using Equation (1) but without weighting.

4.3.2. SoResilere Index Calculation—Categorical Data Subindex

For categorical data results, see Table 5—Categorical Data Optimal Scaling (CATPCA) Component Loadings and Rotated Component Loading Results. The chosen condition was c) with Varimax Rotation (i.e., indicators with values above 0.5 in the module) and the components were classified according to the variable with a higher score. The Dimensions and Components were named according to the Appendix B of Jacinto et al. (2020) (see excerpt in Appendix A). The variable with the highest score in a module or, when very approximate scores, the two variables with the highest scores in the module, are now presented as those variables were selected to assume the main contribution to describe each component of factor and also to label the components.

Component 1 had two variables with scores higher than 0.96. Indicator V4121, which relates to the component Built Environment, Infrastructures and indicator transportation, had the highest score. The variable V4121 was classified according to the evidence found in evacuation routes for disasters and flood events as stated in planning instruments. Variable V3117 relates to Governance, Planning and Governance, Strategies, and the implementation of a strategy to develop adaptive capacity. V3117 is specifically about flood planning. Therefore, this component can be defined as Planning for Flood Evacuation. This component alone accounts for 23.34% of the variance out of the 78.975% variance of the 5 components (see Table 5 for all the percentages of variance of each component).

Component 2 includes variables V3113bi and V3151, the first of which had the higher score. Variable V3113bi is a binary variable and it concerns the inclusion/mention of resilience concepts and strategies in planning instruments. According to Appendices A and C, this variable is related to Governance, Planning and Governance, Strategies, and Set plans. Variable V3151 relates to Governance, Planning and Governance, Risk Governance, and Early Warning, and it evaluates the existence of a municipal warning system or other scale warning systems. The component is globally about Planning for resilience and Risk Governance early warning strategies.

The two variables of Component 3 with higher scores were V3152 and V6112. Variable V3152 is linked to the evidence of prevention strategies in planning instruments and/or local government websites. According to Appendices A and C, this variable relates to Governance, Planning and Governance, Risk Governance, Hazard Prevention and Protection Capacity. Variable V6112 had the second higher score, it substantiates the existence of historical databases or records, and according to Appendices A and C, it refers to Disaster, Learning from the past, Resilience and DRR evaluation, and Learning from previous disaster aid experience. This component can be defined as Disaster Prevention and Lessons Learned.

Component 4 includes only variable V3114bi, which is a binary variable. This variable involves the inclusion of different damage scenarios in planning instruments. V3114bi, according to Appendices A and C, is part of Governance, Planning and Governance, Strategies, and Flexible resilience management systems to handle different types of situations. The component is related to robust planning.

Component 5 includes only variable V3141. This variable is about the use of social media as a way of communication predicted in planning instruments. According to Appendix C, this variable is related to Governance, Planning and Governance, Strategies, Community involvement, and Promoting integrated approaches to livelihoods, disasters and climate change. The component is related to Community engagement promotion in Governance strategies.

Similarly to the calculations applied to the quantitative data in the previous section, the computation of the categorical data was done with and without the weighting component. Equation (2) shows categorical variables in each component. There was no variable negative ponderation as all the variables were collected in a positive ponderation to social resilience.

Equation (2)—Component weighting—categorical data

$$\text{SoResilere} = \left(\frac{V_{3117} + V_{4121} + V_{313bi}}{3}\right) * CP_1 + \left(\frac{V_{3151} + V_{3113bi}}{2}\right) * CP_2 + \left(\frac{V_{3112} + V_{3152} + V_{511} + V_{6112}}{4}\right) * CP_3 + V_{3114bi} * CP_4 + \left(\frac{V_{311} + V_{3141}}{2}\right) * CP_5 \quad (2)$$

where:

V_x are the variables according to Appendix C;

$CP_i \frac{Factor\ x\ \%variance}{Total\%\ cumulative\ variance}$ is the weighting factor of each component for $i = 1, 2, \ldots 5$.

4.3.3. SoResilere—Mapping

SoResilere map classes were defined using the Standard Deviation (Std. Dev.); the same methodology was applied by Cutter et al. (2003) and Guillard-Gonçalves et al. (2015). SoResilere classes for the municipalities were defined by reclassifying the standard deviation into three classes: low (<−0.5 Std. Dev), moderate (−0.5 St. Dev. to 0.5 Std. Dev.) and high (>0.5 Std. Dev). The methodology was the same for both subindexes. The methodology of reclassification based on the standard deviation allowed the comparison and the intersection of the results from the quantitative and categorical subindexes. The final classification with 9 classes was based on the combination of the results of both subindexes, and the classification is described in Table 6.

Table 6. SoResilere final classes.

		Quantitative		
		Low	**Moderate**	**High**
Categorical	Low	Low, Low	Low, Moderate	Low, High
	Moderate	Moderate, Low	Moderate, Moderate	Moderate, High
	High	High, Low	High, Moderate	High, High

5. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5.1. SoResilere—Mapping

The spatial scale in which the data was collected may be discussed, as previously referred. It may be argued that floods in most of the study cases are a phenomenon that affects a very small percentage of the municipalities' territory, as stated by Santos et al. (2020). Nevertheless, the risk governance planning and aid take place at a municipal level, and the majority of the variables are defined at this level. Ideally, a risk questionnaire or a risk-focused census should be implemented so that the data collection method would be applied locally, street by street, which would enable data to be collected at a proper scale. Such data collection would allow the comparison of municipalities' resilience status throughout the country.

Furthermore, the use of data collected via analysis of internet source-based documents is arguable. The consulted internet sources were collected from local government websites and other official organizations. Other authors, such as Summers et al. (2018), also used online sources to collect data which was the only feasible methodology during the COVID-19 pandemic. Nevertheless, this allows us access to the point of view of the population that should be involved in participative planning and resilient disaster risk strategies [14].

5.2. Principal Component Analysis

The requirement of a 60% minimum explained variance [23] set the starting point for the analysis of the variance of the different conditions (Table 1). The sampling adequacy was analyzed, according to Marôco (2021) Marôco (2014), and grouped into KMO classes, <0.5 unacceptable; [0.5; 0.6]—bad but acceptable; [0.6; 0.7]—poor; [0.7; 0.8]—average; [0.8; 0.9]—good; [0.9; 1]—excellent. Only the conditions of Table 1 with sampling adequacy (KMO) higher than 0.75 were kept for further analysis. The cut-off value of 0.75 will show the results that are close to a "good" sampling adequacy (Good KMO—[0.8; 0.9]); according to Marôco (2021), those are also the results with higher rates of variance explained. There were conditions for which the total of the variance explained and sampling adequacy had discrepancies; such was the case of conditions (iii), (iv), (v), (vi), (ix) and (x) in which the rate of variance explained is greater than 70%, especially in condition (x). Nevertheless, those conditions showed lower sampling adequacy (KMO), probably because the number of municipalities was almost the same as the number of variables. Conditions that split the sample into Dimension 1 and Dimension 2 (Appendix B were taken into account. When analyzing the quantitative data separately in Dimension 1 and Dimension 2, results for Dimension 2 present poor sampling adequacy. Therefore, the two dimensions had to be considered jointly in Factor Analysis.

The previous analysis excluded some conditions, and the following will be compared: (i) with (ii) and (vii) with (viii). Since the application of the method of factor rotation, which originated the Rotated Component Matrix, simplifies the analysis of the components and of the variables in each component [37], conditions (i) and (ii) were also excluded. Condition (viii) presents the best sampling adequacy when compared to condition (vii)–(viii) KMO = 0.779 versus (vii) KMO = 0.774), and also the best variance explained (viii) 67.197% versus (vii) 65.771%) for the same 6 factors. The use of Varimax Rotation in the PCA of conditions (vii) and (viii) aimed to simplify the analysis of the loadings as it clearly shows the high loadings allowing us to reduce the number of variables per factor [37,38]. The option was made for a more reliable sample in which all variables are at the municipality level. The difference between the two conditions shows a tendency to increase the adequacy of the sampling when all variables are at the same spatial scale that characterizes each municipality since variables at District and NUTS II may bias the sampling due to the effect of grouping the municipalities. Variables at the district level present the same value as multiple municipalities which are spatially contained in the same District or other generalized special scales, e.g., the NUTS II region.

The results tend to favor the inclusion of variables only at a municipal level. This evidence might set the requirement for future recommendations of data collection at a more detailed scale for all variables, preferably all at the same spatial scale.

According to Table 3, variables V2414 and V2415 and V1331 will be excluded since their loadings are lower than 0.5 in the module and higher than-0.5. Components are built as described in Appendix B. Variables which increase social resilience have positive values, whereas negative values contribute to a decrease in social resilience (i) component 1, (-) V1191, V1192, (-) V1411, V1423, V2413; (ii) component 2, V1181, V1321, V212, V221, V2232; (iii) component 3, (-) V1311, V1313, V143; (iv) component 4, V112, V1182, V1211; (v) component 5, V1322, (-) V222; (vi) component 6, V113, V117, (-) V1321. For a full description of the variables, please see Appendix B—Quantitative Data—Metadata.

Downscaling was achieved by applying the PCA results and loadings obtained from 255 municipalities and assuming these as trends of the 36 municipalities that will be part of the final social resilience index calculation. The reliability of such an approach is based on the fact that the 36 municipalities are part of the 255 municipalities in the analysis. The 36 municipalities make up the set of disaster flood affected that will be part of the final index calculation. We made the hypothesis of downscaling the PCA results of the 255 municipalities as trends of the 36 municipalities that will be part of the final calculation of the social resilience index.

5.3. Optimal Scaling

Three conditions were analyzed (Table 4): (a) 36 municipalities, 12 variables, 12 Dimensions in solution; (b) 36 Municipalities, 12 variables, 5 Dimensions in Solution; (c) 36 Municipalities, 12 variables, 5 Dimensions in Solution with Varimax.

Condition (a) had the maximum number of dimensions or components in the analysis [38], its eigenvalues are greater than 1 up to the fifth component, and Cronbach's Alpha (a measure of the reliability of each dimension in the model) is positive up to the fifth component. These results indicate that the components to be considered for analysis are 5. Conditions (b) and (c) have 5 components; the difference between the results is due to the varimax rotation method applied to condition (c).

Table 5 shows the results of variables by component for conditions (b) and (c). Condition (c), to which the varimax rotation method was applied, produces results that facilitate the selection of variables by dimension because the results (loadings) are more extreme (higher or lower). Taking as an example the result of variable V3151 in condition (b), one could question whether this variable should be included twice or whether to randomly choose the component in which to include it; furthermore, the result under condition (c) is clear for the same variable (v3151). Thus condition (c) will be included in the social resilience index. Categorical data set Optimal scaling results shown in Table 5 are described below as component composition: component 1, V3117, V4121, V313bi; component 2, V3151, V3113bi; component 3, V3112, V3152, V511, V6112; component 4, V2114bi; component 5, V311, V3141. For a full description of the variables, please See Appendix C Metadata for the Categorical Data. In this case, there are no variables with negative weighting because all scales/classifications were set to vary between 0 (less resilient category) and 1 (most resilient category).

5.4. SoResilere Spatial Distribution Analysis

Figures 10 and 11 show the spatial distribution of SoResilere results with and without component weighting factor, respectively. Figure 12 shows the spatial distribution of SoResilere status when comparing Figures 10 and 11 due to component weighting.

Some municipalities maintained their social resilience status (see Figure 12) regardless of the two types of calculations performed, namely, at NUTS II Algarve—Lagoa, Portimão and Silves; at NUTS II Alentejo—Almeirim, Arronches, Benavente and Ourique; at NUTS II Metropolitan Area of Lisbon—Almada, Amadora, Lisbon, Odivelas, Setúbal, Sintra and Vila Franca de Xira; NUTS II Centro—Alenquer, Arruda dos Vinhos, Figueira de Castelo Rodrigo, Pombal, Tomar and Abrantes; NUTS II Norte—Alijó, Carrazeda de Ansiães, Peso da Régua and Vila Nova de Gaia; and NUTS II Azores—Povoação. Of the 36 municipalities in the analysis, 20 (approximately 55.5%) maintained their SoResilere status in both calculations. The municipalities that have a 'high, high' classification on both calculations (Figures 10 and 11) are NUTS II Centro—Pombal; NUTS II Metropolitan Lisbon Area—Alenquer and Lisbon. Municipalities that maintain a 'low, low' SoResiliere score in both calculations are NUTS II Algarve—Portimão and Silves; NUTS II Metropolitan Area of Lisbon—Setúbal; and NUTS II Norte—Vila Nova de Gaia.

Municipalities (distribution according to NUTS II regions) whose classifications changed to a less resilient status (see Figure 12) when a component weighting factor (Figure 10) was used in the calculations compared with no component weighting (Figure 11) in similar calculations were: NUTS II Norte—Porto; NUTS II Metropolitan Area of Lisbon—Oeiras. The analysis of Porto and Oeiras showed that the part of the index responsible for the decrease was, in both cases, the categorical data subindex. In both cases, the status of the categorical data subindex was moderate without component weighting and low with weighting.

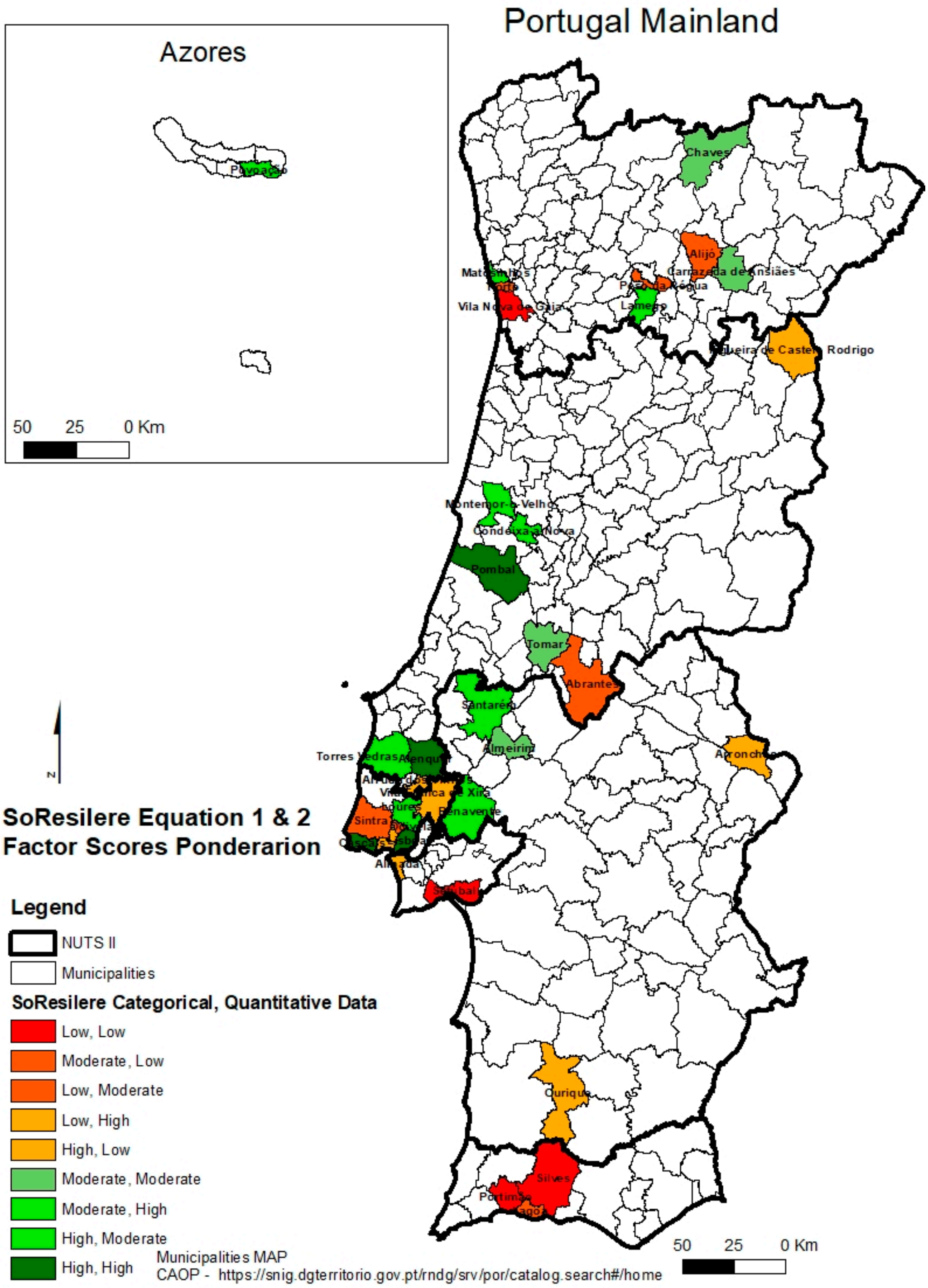

Figure 10. SoResilere Map, Equations (1) and (2), with component weighting.

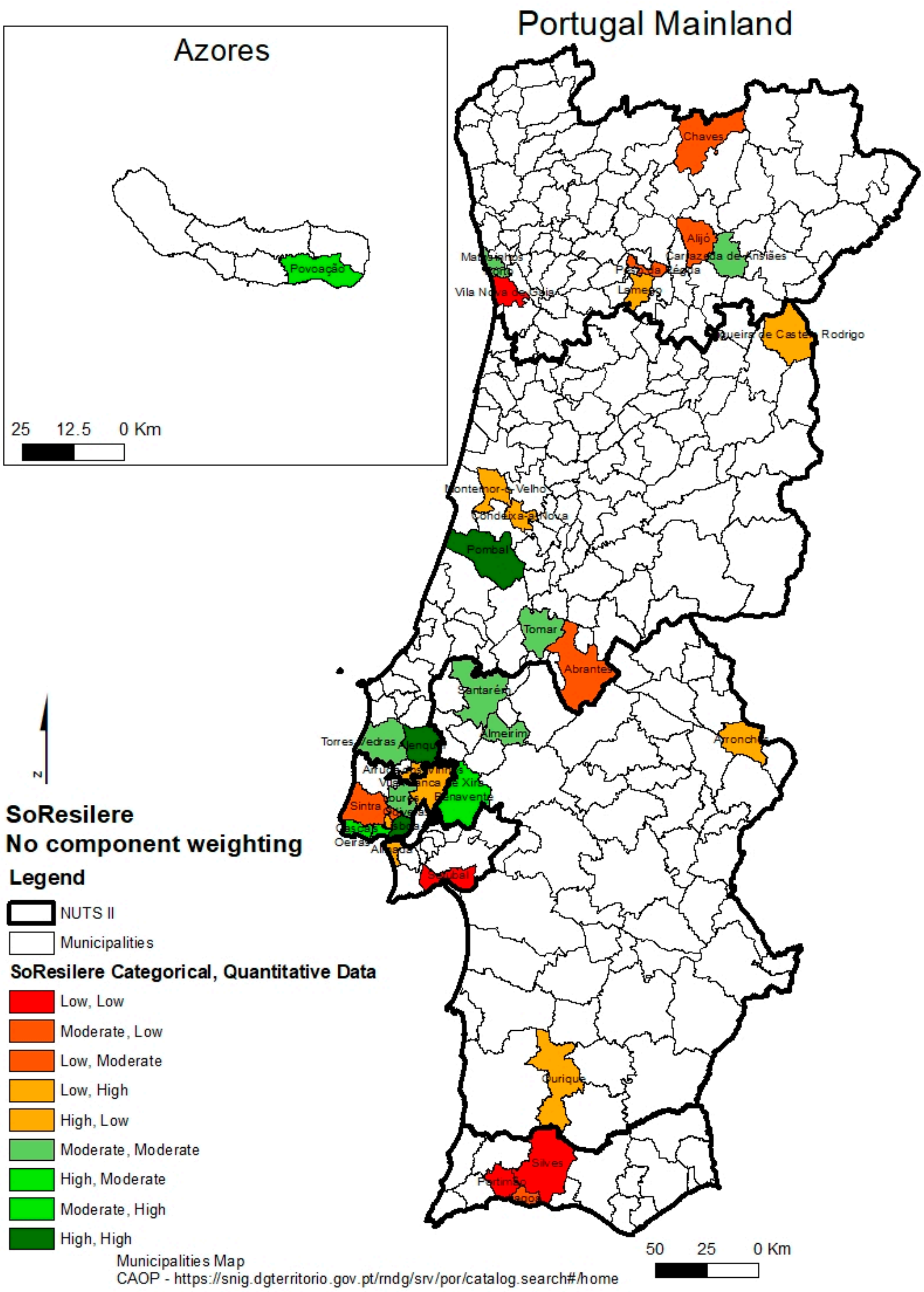

Figure 11. SoResilere Map, no component weighting.

Municipalities (NUTS II regions), whose resilience status changed to a more resilient status (see Figure 12) when a component weighting factor was used in the calculations (Figure 10), were compared with those in which no component weighting factor was used in similar calculations (Figure 11). Those were: NUTS II Norte—Chaves, Matosinhos and Lamego; NUTS II Centro—Condeixa-a-Nova, Montemor-o-Velho and Santarém; NUTS II Metropolitan Area of Lisbon—Loures, Torres Vedras and Cascais. Municipalities in which SoResilere Status improved with component weighting due to the categorical data subindex were: NUTS II Centro—Condeixa-a-Nova (from low to moderate), and Montemor-o-Velho (from low to moderate); NUTS II Metropolitan Area of Lisbon—Loures (from moderate to high). Municipalities in which SoResilere improved with component weighting due to the quantitative data subindex were NUTS II Metropolitan Area of Lisbon—Cascais (from moderate to high); NUTS II Norte—Chaves (from low to moderate), Lamego (from low to moderate), Matosinhos (from moderate to high); NUTS II Centro—Santarém (from moderate to high).

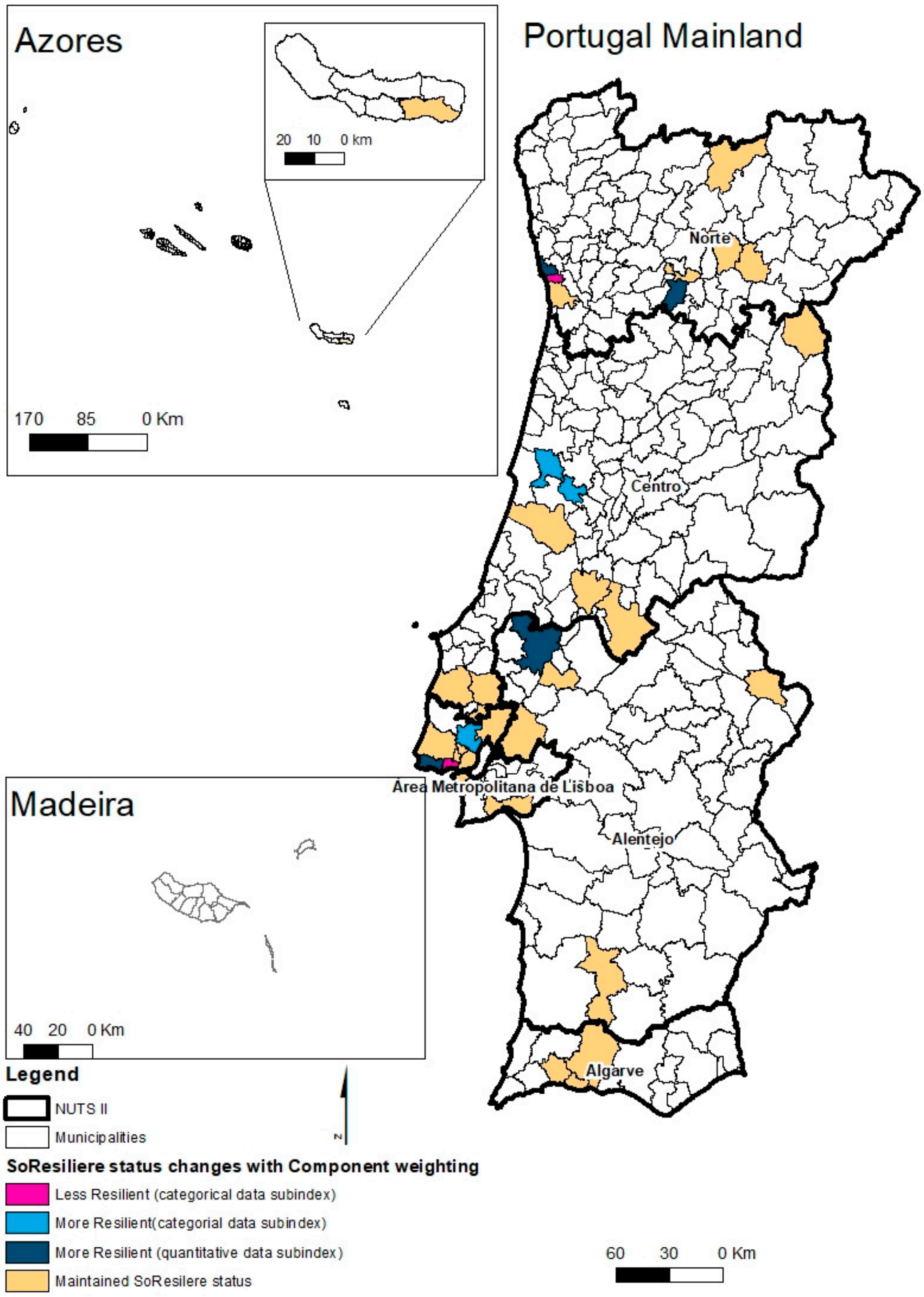

Figure 12. SoResilere Status changes when comparing no weighting (Figure 11) to component weighting (Figure 10).

5.5. SoResilere Discussion

Regarding the SoResilere distribution described in Section 5.4. Component weighting does not make a clear difference to the spatial index distribution. Around 55.5% of the cases maintain their SoResilere status, and 5.55% (2) of the municipalities decreased their status due to the categorical data subindex. Still, component weighting favors the resilience status of the municipalities; 22.22% (8) municipalities had improvement in their SoResilere evaluation. The analysis of which part of the SoResilere contributed to the improvement is not conclusive. From the referred 22.22%, which improved with component weighting, around 13.88% improved due to a better SoResilere on the quantitative data subindex and 8.33% due to the categorical data subindex. In general, component weighting improves the SoResilere status of the municipalities. The quantitative data subindex had an improvement effect when the weighing factor was used. The categorical data increased and decreased the SoResilere status of the municipalities when weighting was used in the calculations. Other studies that applied weighting usually did so on indicators [2,9,22] and not on components; weighting was based either on PCA results [2] or on an expert's judgment [9,22]. Some authors argue that there is no way to establish a hierarchy between the components and indicators in the calculation of indexes by assigning them weights [1,7].

5.5.1. SoResilere Spatial Patterns and Tendencies Analysis

The analysis of SoResilere spatial distribution shows that the delineation of spatial tendencies is fallible and would require further analysis in a larger group of municipalities. Nevertheless, there is a moderate to high SoResilere tendency in the western territory around Lisbon Northern area that irradiates to the Centro region and includes NUTS II Metropolitan Area of Lisbon—Lisbon, Loures, Cascais, Benavente, Alenquer and Torres Vedras and irradiates to NUTS II Centro—Santarém, Alenquer, Tomar and Pombal.

To further the analysis and achieve a new hypothesis, some cross-analysis with previous scientific available studies for the study areas were attempted.

SoResilere comparison with SoVI application to the Lisbon region by Guillard-Gonçalves et al. (2015) was not feasible since Guillard-Goncalves's analysis was performed at the parish level and SoResilere at the municipal level. Municipalities that were analyzed with SoVI and SoResilere were Amadora, Cascais, Lisboa, Loures, Oeiras, Odivelas, and Vila Franca de Xira.

The comparison between SoResiliere spatial distribution and Flood Social Susceptibility Index by Grosso et al. (2015) was not possible since the latter was calculated at the parish level. Social Susceptibility was, in this study, considered a way of describing social vulnerability.

SoResilere spatial distribution was compared with Tavares et al. (2018) social vulnerability in mainland Portugal in 2017. The investigation by Santos et al. (2020) on the main causes of flood risk at the municipal scale included the vulnerability assessment made by Tavares et al. (2020).

Municipalities that have a 'high, high' classification on both calculations of SoResiliere, such as Pombal; Alenquer and Lisbon, had, according to Tavares et al. (2018), moderate, low and very low Social Vulnerability, respectively. Municipalities that maintain a 'low, low' SoResiliere score in both calculations were Portimão, Silves, Setúbal and Vila Nova de Gaia; the same municipalities had a very low, low, very low and low social vulnerability in Tavares et al. (2018) research, respectively. The hypothesis of social resilience and social vulnerability assessment being opposed is partially true in the high, high SoResilere municipalities, although this hypothesis is not confirmed in the 'low, low' SoResiliere municipalities; therefore, any hypothesis based on this analysis is rejected.

The comparison between SoResilere and the Disaster project (http://riskam.ul.pt/disaster/, accessed on 7 December 2022) database of events was not performed, in terms of the consequence of events, as it would be redundant. Hence this database was the origin of the case study selection, and the condition was focused on the consequences of the event. Nevertheless, a comparison of the SoResilere with the recurrence of floods, in terms of the number of days with occurrences, was performed. The comparison was based on the results and conclusions of Lwin et al. (2020), who compared two flood-affected communities, one in a high flood-prone area and another one in a low-prone one; the authors concluded that the community in high flood-prone had more awareness than those in the low-flood prone [14]. We, therefore, searched for the tendency for 'high' status in the categorical part of SoResilere and the frequency of floods. The hypothesis advanced by Lwin et al. (2020) was not confirmed in our study cases. The number of days per study case with occurrences of 'High, High' and of 'Low, Low' in both SoResilere calculations (Figures 10 and 11) were analyzed. In the municipalities that maintained 'High, High' SoResilere—Alenquer, Lisbon and Pombal, there were occurrences in 10, 67 and 6 days, respectively, as registered in the Disaster database. Conversely, in the municipalities that maintained 'Low, Low' SoResilere—Portimão, Setúbal, Silves, and Vila Nova de Gaia—there were 7, 8, 9 and 57 days with occurrences. Hence, the categorical data subindex is the one that can give a better insight into the Governance strategies and include the perception of risk, justifying a broader analysis. The same analysis of the number of days with occurrences in all the municipalities with high on both calculations of the categorical data subindex (with and without component weighting) was performed and compared with all the municipalities with low on both calculations of the categorical data subindex. No pattern could confirm the hypothesis of Lwin et al. (2020) of the high flood-prone zones being the most resilient ones.

Although not all the SoResilere analyzed municipalities are part of the ODS Local project, an attempt was made to compare SoResilere results with the Municipal Sustainable Development Goals Platform (ODS Local—https://odslocal.pt, accessed on 1 March 2022) for the municipalities that were analyzed. The ODS Local available evaluation does not include the same indicators in all municipalities, and the analysis did not succeed.

Uncertainties associated with any index, due to indexes being a simplification of a complex reality [15], are also present in SoResilere. Nevertheless, SoResilere gives decision-makers the knowledge of spatial resilience distribution amongst the flood disaster-affected municipalities in the Portuguese territory. SoResilere is a contribution to a currently unexplored and emergent research field in Portugal.

5.5.2. SoResilere Validation

Validation is an important step in any kind of assessment. However, given the scarcity of available data, it was not possible to validate this social resilience index. To make validation feasible, further data needs to be collected regarding a specific event that affected multiple analyzed municipalities with similar recurrence periods (e.g., 100-year return period) and needs to include the actions done during and immediately after the event and the recovery measures. Another way to perform validation could be the periodic application of SoResilere having the current evaluation as a baseline. Despite the impossibility of applying a validation method, the current SoResilere is an improvement in social resilience knowledge and awareness, namely for decision-makers [15].

Indeed, further work in this research field and the Portuguese context is crucial, namely in what concerns data collection and guidelines for data collection. There are few scientific studies and guidelines regarding who should be responsible for collecting the data for social resilience assessments (governmental, universities, local governments, etc.), the type of instrument used for data collection (questionnaires, interviews, workshops, etc.), the type of data and the adequate scale to collect it. Several studies collected data for their resilience indexes through the application of surveys, questionnaires and interviews [9,12,14,20,22], converting the place-based assessment into a recurrent scientific method for resilience assessment. Such methodologies should be applied in future research in Portugal. The implementation of a disaster risk management census or a database to be built by the local authorities should be put into place by all flood-affected municipalities, as it would improve data quality by reducing bias analysis, providing frequent updating and solving spatial resolution issues.

6. Conclusions

Social resilience assessment is a scientific field in clear expansion, and there is still much to be discussed and tested. Despite the advances in the social resilience assessment that this and other studies present, there is still a long way to go to build indexes that are suitable for the different phases of disaster [5,12].

In the current research, a social resilience index—SoResilere, was built based on Jacinto et al. (2020) database of indicators to assess social resilience. SoResilere is the result of the combination of two parts: the quantitative data subindex and the categorical data subindex. The transposition of the referred database to the Portuguese reality revealed enormous data gaps. This led to the need for data collection and the creation of new indicators. Consequently, there were two types of data quantitative and categorical. Our findings point out that data collection directed to disaster risk should be conceptualized and collected by official entities, either as part of the national Census or by local governments with specific guidelines. Data collection at the municipal level may be more frequent than a census.

The Factor Analysis methodology for data reduction through PCA was applied to quantitative data, and Optimal Scaling was applied to categorical data. Data reduction methods results showed that: (i) in the quantitative data subindex, the components with higher variance explained are related to migration and social networking, the latter with a focus on women empowerment; (ii) the categorical data subindex highlighted the flood planning evacuation, planning for resilience and risk governance early warning strategies. Component weighting has changed SoResilere status in 44.5% of the study cases, of which 22.22% reflected an improvement that was mainly due to the quantitative data subindex.

A cross-analysis with previous academic studies and projects was not successful. Therefore, no validation evidence was found. SoResilere can be regarded as a baseline pioneer study of a social resilience index in Portugal.

Despite the uncertainty associated with indexes, which are data reduction methods to represent and compare complex phenomena and realities, SoResilere is an improvement on the current state of the art. It was based on the current scientific state of the art and the research and findings of Jacinto et al. (2020). SoResilere is a step further in risk governance as it supports decision-makers, raises their awareness of social resilience and provides information on its spatial distribution [2,19] in the Portuguese disaster flood-affected communities.

To improve the current state of the art, further studies should focus on the high quality of data and the adequate spatial and temporal scale. Increasing the data quality will increase index reliability [15]. Whether resilience is to be included in the risk equation and how to implement such inclusion is still a poorly researched issue. This hypothesis should be tested as resilience has been gaining an important role in the disaster risk management field.

Further steps must focus on: (i) guidelines and recommendations on data collection focused on social resilience assessment contributing to resilience governance; (ii) an increase in the number of study cases; and (iii) evaluating the inclusion of Social Resilience into Risk calculations.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

First Proxy Data proposal, including the excluded indicators due to time and scale inadequacy—extracted from Jacinto et al., 2020 Table 3 and Appendix 2.

Appendix 2

Dimension		Category		Indicator		References
nr	Name	nr	Name	General	E.g. data to collect	Based on
1	Individuals	1.1	Psychology - Adaptive Capacity	Confidence	Strong sense of purpose Feels that can achieve goals and/or is the pride of the achievements Prefer to take the lead in problem-solving Positive self-concept	(Bobby Rahman et al., 2016; Davydov et al., 2010; J. J. W. Liu et al., 2017)
				Social skills	Coping style and appraisal (the active coping style in confronting a stressor) The individual and collective response to shocks, stressors, adversity and environmental change	(Bobby Rahman et al., 2016; Tanner et al., 2014)
				Capacity deal with changes and stress, self-control and regulation	Under pressure focus and think clearly Capable of making an unpopular decision Can handle unpleasant feelings Shows capacity to recover from stress, shock and negative events	(Béné et al., 2016; Bobby Rahman et al., 2016; Davydov et al., 2010; J. J. W. Liu et al., 2017; Madewell and Ponce-Garcia, 2016; Tanner et al., 2014)
				Security and feeling of control of own life	Finds meaning in challenging circumstances Effective self-regulation of emotions	(Madewell and Ponce-Garcia, 2016)
				Positiveness	Past success gives confidence for the new challenge Acceptance that things happen for a reason Positive affect, positive emotions such as optimism and humour	(Madewell and Ponce-Garcia, 2016)
				Individual Health	Health behaviours and other key biological indicators Doesn't have special needs/disabilities	(Cutter et al., 2014; Khalili et al., 2015b)
						(Béné et al., 2017; Bobby

Table 3
Summarized database of dimensions and indicators for social resilience assessment.

Dimension	Name	Category		Indicator	References
nr		nr	Name	General	Based on
1	Individuals	1.1	Psychology - Adaptive Capacity	Confidence	(Bobby Rahman et al., 2016; Davydov et al., 2010; Liu et al., 2017b)
				Social skills	(Bobby Rahman et al., 2016; Tanner et al., 2014)
				Capacity to deal with changes and stress, self-control and regulation	(Béné et al., 2017; Bobby Rahman et al., 2016; Davydov et al., 2010; Liu et al., 2017b; Madewell and Ponce-Garcia, 2016; Tanner et al., 2014)
				Security and feeling of control over one's own life	(Madewell and Ponce-Garcia, 2016)
				Positiveness	(Madewell and Ponce-Garcia, 2016)
				Individual health	(Cutter et al., 2014; Khalili et al., 2015a)
				Motivation	(Madewell and Ponce-Garcia, 2016)
				Knowledge	(Béné et al., 2017; Bobby Rahman et al., 2016; Davydov et al., 2010; Khalili et al., 2015a; Madewell and Ponce-Garcia, 2016; Schelfaut et al., 2011; Tyshchuk and Wallace, 2018)
				Sense of belonging	(Davydov et al., 2010; Tyshchuk and Wallace, 2018)
		1.2	Health/disability	Health care	(Cutter et al., 2014; Edwards et al., 2017; Khalili et al., 2015a; Liu et al., 2017b; Madewell and Ponce-Garcia, 2016)
		1.3	Age and Demography	Demography	(Cutter et al., 2014; Davydov et al., 2010; Khalili et al., 2015a)
				Household	(Béné et al., 2017; Kelman, 2017; Khalili et al., 2015a)
				Household resources	(Cutter et al., 2014; Khalili et al., 2015a)
		1.4	Migration	Native language proficiency	(Cutter et al., 2014)
				Place attachment	(Cutter et al., 2014)
				Population diversity	(Cutter et al., 2014; Edwards et al., 2017; Wickes et al., 2017)
2	Society	2.1	Associativism	Volunteerism	(Béné et al., 2017; Butler and Walker-springett, 2016)
		2.2	Social networking	Sense of community & collective efficacy	(Béné et al., 2017; Butler and Walker-springett, 2016; Khalili et al., 2015a; Wickes et al., 2017)
				Community building	(Bobby Rahman et al., 2016; Butler and Walker-springett, 2016; Cutter et al., 2014; Khalili et al., 2015a)
				Informal safety net	(Béné et al., 2017; Butler and Walker-springett, 2016)
		2.3	Institutions	Governance	(Adger, 2000; Béné et al., 2017; Butler and Walker-springett, 2016; Cutter et al., 2014; Schelfaut et al., 2011)
				Interaction involving formal and informal actors	(Adini et al., 2017)
		2.4	Livelihood conditions	Household characteristics	(Adger, 2000; Béné et al., 2017; Cutter et al., 2014; Khalili et al., 2015a; Tanner et al., 2014)
		2.5	Insurance	Insurance capacity	(Cutter et al., 2014; Khalili et al., 2015a)
3	Governance	3.1	Planning and Governance	Strategies	(Adini et al., 2017; Béné et al., 2017; Bobby Rahman et al., 2016; Cutter et al., 2014)
				Policy/governance approach	(Adini et al., 2017; Bobby Rahman et al., 2016; Khalili et al., 2015a; Tanner et al., 2014)
				Community involvement	(Béné et al., 2017; Bobby Rahman et al., 2016; Tanner et al., 2014)
				Research	(Béné et al., 2017; Bobby Rahman et al., 2016; Cutter et al., 2014; I. Kelman et al. 2015)
				Risk governance – prevention	(Adini et al., 2017; Béné et al., 2017; Bobby Rahman et al., 2016; Butler and Walker-springett, 2016)
4	Built Environment	4.1	Infrastructures	Technologies	(Adini et al., 2017)
				Transportation	(Béné et al., 2017; Cutter et al., 2014)
				Services	(Adini et al., 2017; Béné et al., 2017; Cutter et al., 2014)
		4.2	Buildings resistance	Types and conservation of buildings	(Adini et al., 2017; Cutter et al., 2014)
5	Natural Environment	5.1.	Hazard, susceptibility and exposition analysis	Hazard assessment and proxy indicators	(Bobby Rahman et al., 2016; Cutter et al., 2014)
		5.2.	Natural environment		(Adger, 2000; Béné et al., 2017; Cutter et al., 2014)
6	Disaster	6.1	Learning from the past	Resilience and DRR evaluation	(Adini et al., 2017; Béné et al., 2017; Cutter et al., 2014; I. Kelman et al. 2015; Khalili et al., 2015a)
		6.2.	Disasters and recovery	Assistance to citizens	(Adini et al., 2017; Béné et al., 2017)
				Recovery	(Adger, 2000; Bobby Rahman et al., 2016)
				Action during crisis	(Adini et al., 2017; Béné et al., 2017)
				Risk Communication	(Béné et al., 2017)

Source: author's elaboration.

Appendix B. Quantitative Data—Metadata

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Code for PCA and	Spatial Scale	Year	Downloaded from	English Translation	Original Units	Calculations Made	Units	Contribution to the Index	Bibliography
Individuals, Psychology, Confidence	V111	NUTS II	2019	INE	Resident population over 15 years of age (No.) by Place of residence (NUTS—2013), Sex, Age group and Type of chronic disease; Quinquennial—Statistics Portugal, National health survey (series 2014)—Depression	No	% of the population suffering from depression and the % of the population who does not suffer from depression were calculated. Since the indicator reflects a vulnerability and we are calculating resilience we focus on the population that does not suffer from depression as an approximation or sign of confidence.	%	-	[40]
Individuals, Psychology, Social Skills	V112	Municipality	2011	INE	Resident population with at least one disability (No.) by Place of residence (at the date of Census 2011), Sex, Age group and Dimension (persons with special needs); Decennial	No	% of total Pop in the area	%	-	[36]
Individuals, Psychology, Capacity to deal with Changes and Stress, Self-control and regulation	V113	Municipality	2019	INE	Deaths (No.) by Place of residence (NUTS—2013), Sex, Age group and Death cause (European short-list); Annual	No	Percentage of suicide plus Mental and behavioural disorders among the causes of death	%	-	[41]
Individuals, Psychology, Positiveness	V115	NUTS II	2019	INE		No	% of the people per region that are Satisfied or Very Satisfied with their life (level of satisfaction with their life)	%	+	[36]
Individuals, Psychology, Motivation, Strong sense of purpose, work to attain goals, best effort no matter what	V117	Municipality	2018	INE	Births (No.) of Enterprises by Geographic localization (NUTS—2013) and Legal form; Annual—Statistics Portugal, Business demography	No	% of new companies between 2011 and 2018	%	+	[42]
Individuals, Psychology, Knowledge, Know where to turn for help, know how to plan and prioritize, have historical knowledge, level of education	V1181	Municipality	2011	INE	Resident population (No.) by Place of residence (at the date of Census 2011), Sex and Highest completed level of education; Decennial	No	% of the population with a 3rd cycle, secondary, higher and bachelor’s degree	%	+	[43]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Code for PCA and	Spatial Scale	Year	Downloaded from	English Translation	Original Units	Calculations Made	Units	Contribution to the Index	Bibliography
Individuals, Psychology, Knowledge, Access to information and seeking additional information/confirmation. Obtain, propagate and understands warnings	V1182	Municipality	2019	INE	Members of non-governmental organizations for environment per 1000 inhabitants (No.) by Geographic localization (NUTS—2013); Annual	No/1000 inhabitants	None	No/1000 inhabitants	+	[20]
Individuals, Psychology, Sense of Belonging, Religion/spirituality and Normative beliefs (such as perceived expectations of important referent	V1191	Municipality	2011	INE	Resident population over 15 years old (No.) by Place of residence (at the date of Census 2011), Sex, Age group and Marital status; Decennial4	No of population	% of the population with religious beliefs per municipality	%	+	[44]
Individuals, Psychology, Sense of Belonging, Exposure of social media users to normative beliefs (calculated using the co-affiliation network of social media)	V1192	Municipality	2019	INE	Fixed broadband Internet accesses per 100 inhabitants (No.) by Type of access technology to fixed broadband service; Annual—Statistics Portugal, Telecommunications survey	No/100	None	No/100	+	[40]
Individuals, Health/disability, Access to health care and mental health care	V1211	Municipality	2019	INE	Specialized medical doctors (No.) by Place of residence (NUTS—2013), Sex and Medical speciality, subspecialty or competence; Annual—Statistics Portugal, Health personnel statistics	No	% of the resident population that has a medical degree	%	+	[41]
Individuals, Age & Demography, Demography, Age	V1311	Municipality	2019	Pordata	Resident population: total and by major age groups	No	% of the population under 15 and over 65 years old per municipality	%	-	[42]
Individuals, Age & Demography, Demography, Gender	V1312	Municipality	2019	INE	Sex ratio (Males per 100 females) (No.) by Place of residence (NUTS—2013); Annual (2)	No	None	No	-	[4]
Individuals, Age & Demography, Demography, Marital Status	V1313	Municipality	2011	INE	Resident population (No.) by Place of residence (at the date of Census 2011), Sex, Age group, Marital status and Conjugal relationship; Decennial—Statistics Portugal, Population and housing census—2011	No	% of the resident population that is married	%	+	[43]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Code for PCA and	Spatial Scale	Year	Downloaded from	English Translation	Original Units	Calculations Made	Units	Contribution to the Index	Bibliography
Individuals, Age & Demography, Household, Household size and income	V1321	Municipality	2018	INE	Tax household (No.) by Geographic location (NUTS—2013) and Gross reported income less personal income paid class; Annual (2)	No	% above at-risk-of-poverty threshold. Hence the income is presented in breaks of 5k euros, and the threshold is above 6k euros, the option was made to consider the % of the population in each municipality that has an income above 10k as not living at risk of poverty.	%	+	[14]
Individuals, Age & Demography, Household, Household size and income	V1322	Municipality	2011	INE	Private households (No.) by Place of residence (at the date of Census 2011), Sex (reference person of private household), Activity status (reference person of private household) and Type of private household (Based on family nuclei—Census 2011); Decennial	No	% of the active population that is employed per municipality	%	+	[14]
Individuals, Age & Demography, Household Resources, Transportation and communications capacity	V1331	Municipality	2019	INE	Sales of new vehicles per 1000 inhabitants (No.) by Place of residence (NUTS—2013) and Type of vehicle; Annual	No/1000	None	N0/1000	+	[15]
Individuals, Migration, Native Language Proficiency	V1411	Municipality	2019	INE	Foreign population with the legal status of residence (No.) by Place of residence (NUTS—2013), Sex and Nationality (Groups of countries); Annual	No	Subtraction of the foreign population from the total resident population. This result was added to the foreign population originating from countries with Portuguese as an official language and this result was used to calculate the percentage of the total population that is proficient in the Portuguese language.	%	+	[36]
Individuals, Migration, Place attachment, Percentage of residents who are not recent immigrants	V1423	Municipality	2019	INE	Foreign population with the legal status of residence (No.) by Place of residence (NUTS—2013), Sex and Nationality (Groups of countries); Annual	No	% of the total population that requested the status of resident	%	-	[29]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Code for PCA and	Spatial Scale	Year	Downloaded from	English Translation	Original Units	Calculations Made	Units	Contribution to the Index	Bibliography
Individuals, Migration, Population diversity, Races and ethnicity	V143	Municipality	2011	INE	(Difference between) The proportion of the resident population that 1 year before inhabited another territorial unit (%) by Place of residence (at the date of Census 2011); Decennial; and Proportion of the resident population that 5 years before inhabited outside of the municipality (%) by Place of residence (at the date of Census 2011); Decennial	%	Subtract the % of the 5 years before from the % of the 1 year before. The smaller or negative, the more resilient.	%	-	[42]
Society, Associative, Volunteers	V212	Municipality	2019	INE	Firemen (No.) by Geographic localization (NUTS—2013); Annual (2)	No	We opted for the Inhabitants per firefighter indicator, as it reflects better the proportion of the population that volunteers in order to compare between municipalities. In Pordata we can find this indicator "Where are there more and fewer people, on average, per professional or volunteer firefighter?"	No	-	[20]
Society, Social Networking, Sense of community & Collective efficacy	V221	Municipality	2017	SIGMAI/Pordata	Abstention rate in the elections for the Local Authorities	%	None	%	-	[15]
Society, Social Networking, Community Building	V222	Municipality	2012	Pordata	Unemployment registered at the public employment office in a total of the resident population aged 15 to 64 years (%)	%	None	%	-	[36]
Society, Social Networking, Informal Safety Net, informal safety net (non-governmental organizations, associations, institutions)	V2231	District	2018	INE	Practitioners affiliated (No.) to sports federations by Geographic localization (Distrito) and Sex; Annual (1): Resident population (No.) by Place of residence (NUTS—2013), Sex and Age group; Annual	No	% of the total population that is subscribed to sports federations	%	+	[15]
Society, Social Networking, Informal Safety Net, women empowerment	V2232	Municipality	2018	Pordata	Employees in Local Government: total and by sex	No	% of women working in public administration	%	+	[20]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Code for PCA and	Spatial Scale	Year	Downloaded from	English Translation	Original Units	Calculations Made	Units	Contribution to the Index	Bibliography
Society, Livelihood conditions, Household Characteristics, Promotion of economic vitality: employment and homeownership/right to housing and property; non-reliance on a narrow range of resources; equality of income distribution among the population (across races/ethnicities and genders).	2413	Municipality	2019	INE	New recipients of unemployment benefits of social security (No.) by Place of residence (NUTS—2013) and Sex; Annual (1)	No	% of the resident population who are new beneficiaries of Social Security	%	-	[23]
Society, Livelihood conditions, Social/Human Rights: Access/right to medical care; Right to housing and property; Food Security/Right to food; Access to social services	2.4.1.4	Municipality	2011	Pordata	Conventional dwellings of usual residence, according to the Census: total, by homeowner-occupier and tenants	No	% of homeowners	%	+	[21]
Society, Livelihood conditions, Recorded Crime Rates	2.4.1.5	Municipality	2019	INE	Registered crimes (No.) by the police authorities by Geographic localization (NUTS—2013) and Category of crime; Annual (3)	No	None	No	-	[36]

Appendix C. Metadata for the Categorical Data

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Variable Code	Generated Indicators (Data Sources: Adapt PT Project—https://www.adapt-local.pt/ (accessed on 7 December 2022), Municipal Emergency and Civil Protection Plans, Municipal Director Plans, Special Flood Plans, Local Governments Websites)	Hypothesis (Current Hypothesis Were Created According to the Reality with the Information in Plans and Websites Available Online in the Period between:)—All Hypothesis Have Been Posed so that 0 Is the Less Resilient and 1 the Most Resilient, Therefore	Bibliographic Reference
Governance, Planning and Governance, Strategies, Positive coping strategies	V3111	Carrying out Flood Exercises (the carrying out of exercises is the district's responsibility)	0—No exercises in the past and no exercises planned for the future, or the information is not available; 0.25—There were exercises but the local government was not responsible, and/or there are plans for future exercises in a Flood Special plan but no mention in the Municipal Emergency and Civil Protection Plan; 0.5—The Municipal Emergency and Civil Protection Plan refers a date for an exercise related to flood or meteorological adverse situations but there is no way to confirm if the exercise took place 0.75—Yes, exercises of simulation of floods or adverse meteorological situations occurred although there are no reports of lessons learnt registered; 1—There are regular exercises concerning floods or adverse meteorological situations organized by the local government or in coordination between the local government and other entities with connection with the Municipal Emergency and Civil Protection Plan.	[11,12,34,45]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Variable Code	Generated Indicators (Data Sources: Adapt PT Project—https://www.adapt-local.pt/ (accessed on 7 December 2022), Municipal Emergency and Civil Protection Plans, Municipal Director Plans, Special Flood Plans, Local Governments Websites)	Hypothesis (Current Hypothesis Were Created According to the Reality with the Information in Plans and Websites Available Online in the Period between:)—All Hypothesis Have Been Posed so that 0 Is the Less Resilient and 1 the Most Resilient, Therefore	Bibliographic Reference
Governance, Planning and Governance, Strategies, Sustainable adaptive and/or transformative strategies	V3112	Does planning include long-term scenarios?	0—Planning does not comprise long term scenarios, there are no climate change strategies and/or climate change scenarios and/or adaptation measures for the municipality; 0.25—Municipal Climate Change Adaptation Plan under development in cooperation with a research team of a company or under development of flood risk maps or there is already a Climate Change plan that includes the municipality, but it is not at municipal level; 0.5—A Plan at regional/or other scale which comprises the municipality and includes adaptation measures although does not specify scenarios or return periods or there are no specific measures for floods or the Municipal Emergency and Civil Protection Plan presents a flood plain map with no indication of the return period; 0.75—There is a Regional or other scale Adaptation Plan that is referred in the Municipal Emergency and Civil Protection Plan (there's coordination between two levels of planning), or there's an Municipal Adaptation Plan (more recent than the municipal Emergency and Civil Protection Plan) with no connection with the Emergency and Civil Protection Plan or the Emergency and Civil Protection Plan mentions that the floodable areas have a 100 y-return period; 1—Has a robust planning: the plans comprise scenario (flooding scenarios) and climate change scenarios and/or how the climate will evolve in long term with more than 100y-return periods (e.g., 1000 years) or The Municipal Adaptation and/or Emergency and Civil Protection Plans comprise climate change scenarios.	[11,12,34,45]
Governance, Planning and Governance, Strategies, Set plans: flood management plans; emergency response plans; plan for reinforcement of resources in resilience management	V3113bi	Does planning include resilience?	0—No references to resilience or to promote it amongst the information found online; 1—The Municipal Emergency and Civil Protection Plan and/or the Adaptation Plans which comprise the Municipality do mention actions to promote resilience focusing on Flood; or a specific project of resilience (e.g., RESCUE) includes floods and the municipality.	[11,12,34,45]
Governance, Planning and Governance, Strategies, and Flexible resilience management systems to handle different types of situations	V3114bi	Does planning include different damage scenarios?	0—No references to damages or losses in the municipal level plans or the information is not available; 1—Planning (Municipal Emergency and Civil Protection Plan and/or the Adaptation Plans are Regional or other scales) include real or modelled flood scenarios, or the Municipality has a specific Resilience project.	[11,12,34,45]
Governance, Planning and Governance, Strategies, Set an adaptive capacity developing strategy	V3117	There is a specific flood planning?	0—No reference/no planning to prepare/face floods or meteorological adverse conditions or the information is not available; 0.25—There is no specific flood plan but the Municipal Director Plan had different articles that mention flooding area; 0.5—There is a flood plan which comprises the municipality, but is not at municipal lever; 0.75—The Municipal Emergency and Civil Protection and/or The Municipal Climate Change Adaptation contain specific articles/measures or mention floods; 1—Has a Municipal Flood Plan or Averse Meteorological Situations Plan or includes a full section dedicated to flood in the Municipal Emergency and Civil Protection Plan.	[11,12,34,45]
Governance, Planning and Governance, Strategies, Community involvement, Promoting integrated approaches to livelihoods, disasters and climate change	V313bi	Municipal participatory budget?	0—No reference to the Municipal Participatory Budget was found or the last reference was previous to 2019; 1—There is a specific updated website dedicated to the Participatory Budget or there is evidence of a current or 2020/21 Participatory Budget	[11,33,34]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Variable Code	Generated Indicators (Data Sources: Adapt PT Project—https://www.adapt-local.pt/ (accessed on 7 December 2022), Municipal Emergency and Civil Protection Plans, Municipal Director Plans, Special Flood Plans, Local Governments Websites)	Hypothesis (Current Hypothesis Were Created According to the Reality with the Information in Plans and Websites Available Online in the Period between:)—All Hypothesis Have Been Posed so that 0 Is the Less Resilient and 1 the Most Resilient, Therefore	Bibliographic Reference
Governance, Planning and Governance, Research, Evaluate readiness to cope with crisis	V3141	Social media are included as a way of communication/tool in the planning instruments.	Note: In this indicator, all internet-based communications. 0—No references found about internet-based communication in the Municipal Plans or Local Government website; 0.25—There are references but not at the municipal level (regional, district etc.) that refer to the municipality (for instance in Special Floods Plans and—Climate Change Strategies at other geographic scales); 0.5—There are references on the local government website; 0.75—There are references to internet-based communications (websites, Facebook etc.) in Municipal Plans such as Director Municipal Plan, or Local Government website but not found on the Municipal Emergency and Civil Protection Plan; 1—There are references on the Municipal Emergency and Civil Protection Plan of the usage of the website ADN other internet-based means (Facebook, Instagram, etc.).	[7,33,34,46]
Governance, Planning and Governance, Risk Governance, Early Warning	V3151	Municipal warning system? Usage of regional or national warning systems?	0—Municipal Emergency and Civil Protection Plan and Special Floods Plan and Local Government Website don't mention warning systems for the municipality; 0.25—A reference to a warning system was found but not in the municipal level plan (e.g., a Special Floods Plan at the regional level, website, etc.); 0.5—The Municipal Emergency and Civil Protection Plan refer the use of a national level warning system; 0.75—The Municipal Emergency and Civil Protection Plan refers the use of a national level warning system and the intension to invest in a regional/municipal level warning system the evidence of such intention might be found in the local government website or local newspaper websites or online sources related to the municipality participation in regional projects; 1—The Local Government has invested and has a local/municipal floods warning system.	[33,34,45,47]
Governance, Planning and Governance, Risk Governance, Hazard prevention and protection capacity	V3152	Planning and/or website refer prevention strategies?	0—There are no references to prevention strategies or actions; 0.25—There are prevention actions/measures and strategies but are not specific for floods; 0.5—There are references to prevention actions/measures and strategies to floods but not specifically in Risk/Floods or in the Municipal Emergency and Civil Protection Plan; 0.75—There are clear and specific prevention actions/measures and strategies to floods in the local Government plans (e.g., Municipal Emergency and Civil Protection Plan, Municipal Director Plan etc) but those measures have no timeline; 1—There are clear and specific prevention actions/measures and strategies and Programmes to floods prevention in the local Government website or other documents with timeline, target groups specification and/or there are guidelines that are available for the population but might not be part of Municipal Emergency and Civil Protection Plan or Special Floods Plan; and/or Municipal Emergency and Civil Protection Plan/Special Floods Plan does have the timeline plan with actions for flood prevention.	[33,34,45,47]
Built Environment, Infrastructures, Transportation.	V4121	Plans and/or website refer to evacuation routes?	0—The information is not available or was not present on the Municipal Emergency and Civil Protection Plan nor on the local government website or the only reference is that the evacuation is a police/military task; 0.25—Some routes are referred or mapped but they are not specifically for floods; 0.5—There are evacuation routes **and** population agglomeration places and that are referred and mapped but they are not specifically for floods; 0.75—There are evacuation routes **or** population agglomeration places and that are referred and mapped; 1—There are evacuation routes and population agglomeration places and that are referred and mapped.	[7,33]

Dimension, Component, and Indicators According to Jacinto, Reis & Ferrão (2020) [5]	Variable Code	Generated Indicators (Data Sources: Adapt PT Project—https://www.adapt-local.pt/ (accessed on 7 December 2022), Municipal Emergency and Civil Protection Plans, Municipal Director Plans, Special Flood Plans, Local Governments Websites)	Hypothesis (Current Hypothesis Were Created According to the Reality with the Information in Plans and Websites Available Online in the Period between:)—All Hypothesis Have Been Posed so that 0 Is the Less Resilient and 1 the Most Resilient, Therefore	Bibliographic Reference
Natural Environment, Hazard, susceptibility and exposition analysis, Hazard assessment and proxy indicators	V511	The regulation prohibiting building inside flooding areas	0—There was a land use status change and/or authorization for construction in an Area Threatened by Floods after the definition of the National Ecological Network (REN) without any intervention to defend against the floods; 0.25—There was a land use status change for Construction and/or approval of new constructions as a result of being considered safe after regularization or to legalize previously existing constructions; 0.5—There was land use status change for regularization; 0.75—There was land use status change of areas threatened by floods for agricultural practice or landscape requalification; 1—There was no land use status change of an area threatened by floods in the last or two last REN updates.	[7,34]
Disaster, Learning from the past, Resilience and DRR evaluation, Learning from previous disaster aid experience	V6112	Existence and/or reference of a historical database of events.	0—No reference; 0.25—Refers to the date of the biggest flood or the last flood episode but without details; 0.5—Has reference to the biggest floods for years but no details; 0.75—Describes in detail at least 1 full episode; 1—Has an inventory with floods for periods/decades/years over time and details of affected locations and/or water height and/or affected population, etc.	[7,12,33,45,46]

Appendix D. Total Variance Explained and Component Matrix from Conditions: (i), (ii) and (vii)

Condition (i) 27 variables and 255 municipalities.

Table A1. Total Variance explained (extract) from (i) 27 variables and 255 municipalities.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.462	23.934	23.934	6.462	23.934	23.934
2	3.200	11.850	35.784	3.200	11.850	35.784
3	2.694	9.978	45.762	2.694	9.978	45.762
4	2.370	8.779	54.541	2.370	8.779	54.541
5	1.615	5.983	60.524	1.615	5.983	60.524
6	1.417	5.247	65.771	1.417	5.247	65.771
7	1.053	3.900	69.672	1.053	3.900	69.672
8	0.992	3.675	73.347			
9	0.932	3.454	76.800			

Total Variance Explained. Extraction Method: Principal Component Analysis.

Table A2. Component Matrix from (i) 27 Variables and 255 Municipalities.

	Component						
	1	2	3	4	5	6	7
Zscore(V111NUTS II)	−0.453	0.554	0.342	−0.285	−0.063	−0.183	−0.099
Zscore(V112)	0.621	0.187	0.214	0.434	0.182	−0.178	0.256
Zscore(V113)	0.057	0.118	0.028	0.548	−0.020	0.233	−0.242
Zscore(V115NUTS II)	−0.124	0.177	−0.540	0.431	0.444	0.218	0.264
Zscore(V117)	−0.244	−0.578	−0.041	0.355	0.151	0.164	−0.104
Zscore(V1181)	0.868	0.146	0.294	0.014	0.028	0.087	−0.065
Zscore(V1182)	0.040	−0.104	0.324	0.232	0.262	−0.387	0.448
Zscore(V1191)	−0.721	0.144	−0.198	0.286	0.280	0.021	0.053
Zscore(V1192)	0.850	−0.270	0.044	−0.213	0.145	−0.027	−0.074
Zscore(V1211)	0.542	0.153	0.293	0.285	0.368	−0.312	−0.082
Zscore(V1311)	−0.273	−0.478	0.588	0.201	−0.188	−0.221	−0.027
Zscore(V1312)	−0.006	0.114	−0.109	−0.633	−0.073	0.068	0.368
Zscore(V1313)	0.245	0.693	−0.344	−0.102	0.011	0.232	0.077
Zscore(V1321)	0.582	0.377	0.494	−0.229	−0.043	0.029	−0.147
Zscore(V1322)	−0.395	0.063	0.563	−0.236	0.412	0.327	0.043
Zscore(V1331)	0.435	−0.108	0.028	−0.059	0.460	0.082	−0.213
Zscore(V1411)	−0.483	0.769	0.093	0.189	0.013	−0.055	−0.102
Zscore(V1423)	0.599	−0.685	0.000	−0.058	−0.005	0.066	0.117
Zscore(V143)	0.223	0.378	−0.235	−0.139	0.166	−0.428	−0.302
Zscore(V212)	0.618	0.292	0.009	0.301	−0.122	0.176	0.036
Zscore(V221)	0.627	0.038	0.089	0.154	0.022	0.329	−0.257
Zscore(V222)	0.192	0.002	−0.586	0.422	−0.364	−0.343	−0.066
Zscore(V2231Dist)	−0.011	−0.216	−0.437	−0.307	0.510	0.053	−0.228
Zscore(V2232)	0.408	0.150	0.130	0.247	−0.381	0.466	0.171
Zscore(V2413)	0.569	−0.156	−0.485	−0.341	−0.149	−0.082	−0.036
Zscore(V2414)	−0.762	−0.180	0.125	−0.033	−0.017	0.259	−0.102
Zscore(V2415)	0.400	0.181	−0.089	−0.198	0.162	0.058	0.358

Component Matrix [a]. Extraction Method: Principal Component Analysis.
[a]. 7 components extracted.

Condition (ii) 24 variables (excluding NUTS II and District level indicators) and 255 municipalities.

Table A3. Total Variance explained (extract) from (ii) 24 variables (excluding NUTS II and District level indicators) and 255 municipalities.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.273	26.137	26.137	6.273	26.137	26.137
2	2.880	11.999	38.136	2.880	11.999	38.136
3	2.376	9.901	48.037	2.376	9.901	48.037
4	2.055	8.563	56.600	2.055	8.563	56.600
5	1.417	5.902	62.503	1.417	5.902	62.503
6	1.127	4.694	67.197	1.127	4.694	67.197
7	0.959	3.997	71.194			
8	0.884	3.685	74.879			
9	0.868	3.616	78.495			
Extraction Method: Principal Component Analysis.						

Table A4. Component Matrix from Factor Analysis condition (ii) 24 variables (excluding NUTS II and District level indicators) and 255 municipalities.

Component Matrix [a]						
	Component					
	1	2	3	4	5	6
Zscore (V112)	0.631	0.065	0.426	0.269	0.217	−0.114
Zscore (V113)	0.060	0.081	0.275	0.460	−0.251	0.407
Zscore (V117)	−0.291	−0.544	0.032	0.311	−0.080	0.353
Zscore (V1181)	0.879	0.017	0.278	−0.103	−0.086	−0.007
Zscore (V1182)	0.039	−0.204	0.390	0.088	0.438	−0.263
Zscore (V1191)	−0.710	0.208	0.082	0.229	0.117	0.193
Zscore (V1192)	0.833	−0.327	−0.091	−0.184	0.082	0.076
Zscore (V1211)	0.559	0.011	0.465	0.138	0.398	0.077
Zscore (V1311)	−0.300	−0.590	0.404	0.068	0.051	−0.268
Zscore (V1312)	0.012	0.132	−0.377	−0.576	−0.008	−0.093
Zscore (V1313)	0.288	0.744	−0.173	−0.051	−0.147	0.162
Zscore (V1321)	0.612	0.238	0.389	−0.375	−0.064	−0.153
Zscore (V1322)	−0.374	−0.066	0.502	−0.588	−0.070	0.278
Zscore (V1331)	0.431	−0.155	0.067	−0.124	0.165	0.598
Zscore (V1411)	−0.430	0.761	0.349	0.077	0.055	−0.043
Zscore (V1423)	0.552	−0.719	−0.203	−0.005	−0.071	0.033
Zscore (V143)	0.258	0.378	−0.189	0.008	0.468	0.255
Zscore (V212)	0.630	0.242	0.173	0.239	−0.230	−0.072
Zscore (V221)	0.627	−0.022	0.179	0.104	−0.338	0.138
Zscore (V222)	0.175	0.134	−0.431	0.733	0.121	−0.126
Zscore (V2232)	0.412	0.092	0.171	0.160	−0.618	−0.167
Zscore (V2413)	0.559	−0.077	−0.650	−0.038	0.017	0.010
Zscore (V2414)	−0.772	−0.141	0.087	−0.092	−0.247	0.064
Zscore (V2415)	0.413	0.159	−0.100	−0.249	0.090	0.006
Extraction Method: Principal Component Analysis.						
[a]. 6 components extracted.						

Condition (vii) 27 Variables, 255 Municipalities with Varimax Rotation

Table A5. Total Variance Explained (extract) from (vii) 27 Variables, 255 Municipalities with Varimax Rotation.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.462	23.934	23.934	6.462	23.934	23.934	5.343	19.790	19.790
2	3.200	11.850	35.784	3.200	11.850	35.784	3.535	13.094	32.884
3	2.694	9.978	45.762	2.694	9.978	45.762	2.374	8.792	41.677
4	2.370	8.779	54.541	2.370	8.779	54.541	2.309	8.553	50.230
5	1.615	5.983	60.524	1.615	5.983	60.524	2.011	7.447	57.677
6	1.417	5.247	65.771	1.417	5.247	65.771	1.641	6.076	63.753
7	1.053	3.900	69.672	1.053	3.900	69.672	1.598	5.919	69.672
8	0.992	3.675	73.347						
9	0.932	3.454	76.800						
Extraction Method: Principal Component Analysis.									

Table A6. Rotated Component Matrix from Factor Analysis condition (vii) 27 variables and 255 municipalities with Varimax Rotation.

Rotated Component Matrix							
	Component						
	1	2	3	4	5	6	7
Zscore (V111NUTS II)	−0.058	−0.777	0.248	−0.193	−0.216	−0.052	0.051
Zscore (V112)	0.551	0.065	−0.153	0.184	0.177	0.607	−0.142
Zscore (V113)	0.114	−0.072	−0.050	0.125	0.600	−0.043	−0.182
Zscore (V115NUTS II)	−0.329	0.041	−0.062	0.774	0.288	0.199	0.058
Zscore (V117)	−0.391	0.431	0.129	−0.126	0.458	0.018	0.030
Zscore (V1181)	0.903	0.185	−0.024	0.061	0.013	0.114	−0.094
Zscore (V1182)	−0.026	0.044	0.083	−0.116	−0.041	0.752	−0.024
Zscore (V1191)	−0.672	−0.334	0.153	0.237	0.280	0.098	0.110
Zscore (V1192)	0.692	0.561	−0.094	−0.012	−0.155	0.054	0.202
Zscore (V1211)	0.591	−0.018	−0.046	0.008	0.242	0.510	0.229
Zscore (V1311)	−0.189	0.099	0.190	−0.743	0.205	0.256	−0.178
Zscore (V1312)	−0.038	−0.004	0.117	0.150	−0.717	−0.131	−0.041
Zscore (V1313)	0.294	−0.348	−0.149	0.653	−0.173	−0.196	−0.073
Zscore (V1321)	0.837	−0.195	0.158	−0.106	−0.150	0.000	−0.064
Zscore (V1322)	−0.083	−0.187	0.872	−0.064	−0.023	0.043	0.042
Zscore (V1331)	0.411	0.297	0.165	0.154	0.126	0.045	0.378
Zscore (V1411)	−0.142	−0.889	0.079	0.179	0.177	0.012	−0.053
Zscore (V1423)	0.284	0.852	−0.083	−0.150	−0.082	0.084	−0.026
Zscore (V143)	0.283	−0.315	−0.344	0.109	−0.081	0.009	0.503
Zscore (V212)	0.586	0.034	−0.223	0.291	0.177	0.065	−0.301
Zscore (V221)	0.638	0.244	0.000	0.151	0.282	−0.157	−0.086
Zscore (V222)	−0.088	0.050	−0.866	0.103	0.199	0.012	−0.045
Zscore (V2231Dist)	−0.138	0.295	0.089	0.277	−0.060	−0.211	0.639
Zscore (V2232)	0.393	0.110	−0.038	0.181	0.116	−0.113	−0.657
Zscore (V2413)	0.297	0.415	−0.470	0.152	−0.363	−0.246	0.183
Zscore (V2414)	−0.614	−0.135	0.423	−0.201	0.149	−0.257	−0.065
Zscore (V2415)	0.298	0.116	0.009	0.371	−0.354	0.176	−0.031
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
Rotation converged in 12 iterations.							

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