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Territorial vulnerability to natural hazards in Europe: a composite indicator analysis and relation to economic impacts

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Abstract
This article presents an assessment of territorial vulnerability to natural hazards in Europe at the regional level (NUTS3). The novelty of the study lies in assessing vulnerability to natural hazards through a composite indicator analysis over a large extension (1395 territories in 32 different countries), and in analysing the relation between vulnerability and economic impacts of past disasters. For responding to the first goal, a principal component analysis (PCA) was performed over 25 indicators, previously grouped into susceptibility and coping capacity, and subsequently combined to obtain the final vulnerability. The main result is the spatial distribution of vulnerability to natural hazards across Europe through a normalised and comparative approach, which indicates that 288 out of 1395 regions presented a high or a very high level of vulnerability. They are concentrated in Eastern and Southern Europe, and in the Baltic Region, and the sum of their population lives in territories with high or very high vulnerability level, representing 20% of the total sample, i.e. 116 out of 528 million inhabitants. Regarding the methodology for analysing the relation between vulnerability and economic impacts, a spatial regression model has been used to combine hazard, exposure and vulnerability. The outcomes indicate a high level of agreement between vulnerability and the distribution of past economic impacts, which confirm that the indicator-based approach is a good proxy for assessing vulnerability to natural hazards. Knowing the distribution of vulnerability is of high relevance for targeting disaster risk management and climate change adaptation actions to the highest priority regions.

Keywords Europe · Natural hazards · NUTS3 · PCA · Spatial regression model · Vulnerability

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1 Introduction

Territorial vulnerability to natural hazards is understood as the condition determined by physical, social, economic and environmental factors or processes that increase the susceptibility of a territory to the impacts of hazards (UN 2016). The concept of vulnerability explains the fact that comparable levels of hazard and exposure produce different levels of impact in different territories, making the impacts of natural hazards unevenly distributed across space. The likelihood of such impacts occurring is known as risk and is thus divided into three components: hazard, exposure and vulnerability (UNDRR 2019). While the hazard is physically determined, exposure and vulnerability are socially constructed and related to socioeconomic inequalities (Cutter et al. 2003; Brooks et al. 2005; Myers et al. 2008; Tate et al. 2016; Barreca et al. 2017).

The concept of vulnerability is complex and encompasses multiple dimensions that require a holistic and integrative approach to be understood (Blaikie et al. 1994; Birkmann 2013). In this regard, the assessment presented here considers the following eight dimensions: demography, education and research, economy, environment, social capital, risk perception, gender and governance. Moreover, the selected indicators are disaggregated by those that increase territorial vulnerability, e.g. susceptibility, and those that decrease it, e.g. coping capacity. The considered set of indicators, defined based on a literature review and data availability, attempts to capture the complexity associated with the triggering of a disaster after the occurrence of a natural hazard.

There are a wide range of approaches to analyse vulnerability to natural hazards (Birkmann 2013), some of which consider the physical vulnerability of assets or infrastructure, while others consider socioeconomic and demographic vulnerability; moreover, vulnerability can be assessed using both quantitative and qualitative methodologies (Conlon et al. 2020). The approach followed acknowledges the traditional analysis of vulnerability, which considers its multiple dimensions—social, economic and environmental–and is characterised by a set of indicators, together culminating in a composite index. The final index is obtained through the implementation of statistical techniques, in this case, principal component analysis (PCA), which is considered a powerful statistical technique for analysing high-dimensional data by summarising a set of indicators while preserving the maximum possible proportion of the total variation in the original dataset (Nardo et al. 2008).

The vulnerability assessment carried out in this research is placed in the context of the ESPON-TITAN project, territorial and economic impacts of selected natural hazards in Europe (Greiving and Navarro, this issue). Alongside the vulnerability analysis, the territorial patterns of selected natural hazards (Klein et al. this issue), direct and indirect economic impacts of disasters (Petsinaris et al. this issue), disaster risk management of selected natural hazards in Europe (Blecking et al. this issue; Fleischhauer et al. this issue) and a comparative study of selected European case studies (Farinós et al. this issue) have been analysed.

A comparable project in terms of having the same geographical scope (countries belonging to the ESPON space) and being at the provincial level (NUTS3) is ESPON NATURAL HAZARDS (ESPON 2006). In that project, an analysis of vulnerability to natural hazards was also carried out using an indicator-based approach. Although the results of that project were of great interest, today they have some drawbacks due to the outdatedness of data and the use of a reduced number of indicators.

This study has been guided by the following two research questions that were formulated based on the needs identified in ESPON-TITAN to update the existing vulnerability assessment with new data and to relate it to the economic impacts of disasters.

- Which territories are most vulnerable to natural hazards in Europe at NUTS3?
- Is there any relationship between vulnerability to natural hazards and the distribution of past economic impacts due to natural hazards?

The aim of this research is to respond to the previous research questions. Regarding the territorial vulnerability to natural hazards in Europe, the 32 countries[1] belonging to the ESPON space have been considered, resulting in 1395 territories at NUTS3, and it is assessed through an indicator-based methodology using PCA. To address the second research question, a spatial regression model is applied to analyse the relationship between territorial vulnerability and past economic impacts. The natural hazards included are river floods, storms, droughts, earthquakes and landslides (Klein et al. this issue), and for past economic impacts due to natural hazards, the sum of direct and indirect impacts collected from an input–output model (Petsinaris et al. this issue) is considered.

There are numerous studies, as discussed in the following section, where PCA is applied to assess vulnerability to natural hazards which indicates that it is a robust and consistent methodology for assessing vulnerability. The novelty of this study is that there are no other studies, or at least the authors are not aware of, where PCA methodology is applied to assess vulnerability to natural hazards across Europe and at the NUTS3 scale. Another novel aspect arises from combining vulnerability with hazard and exposure to analyse the contribution of vulnerability to explaining the distribution of past economic impacts.

2 Vulnerability assessment based on composite indicators

In this research, vulnerability is represented by a set of indicators that are reduced to components using PCA, which is a powerful statistical technique for analysing high-dimensional data and then aggregated to obtain a composite index. This technique allows the reduction of data dimensionality, obtaining data patterns and enabling the identification of aspects that make a territory especially vulnerable to natural hazards (Oppio et al. 2017; Frigerio and Amicis 2016; Kotzee and Reyers 2016; Conlon et al. 2020; Yu et al. 2021).

Vulnerability assessment through composite indicators has been successfully applied in numerous studies, as further presented. Since Cutter et al. (2003) proposed the Social Vulnerability Index (SoVI) to measure vulnerability to environmental hazards, interest in this field has grown significantly (Liu and Li 2016). Cutter et al. (2003) assessed vulnerability to hazards in the USA at the county level using PCA, with 42 independent variables and combined the extracted components using equal weight. From those variables, 11 components are obtained, accounting for 76.4% of the variance in the original data. It is important to state that the captured vulnerability at the county level was hazard independent. A more recent case of SoVI implementation (de Loyola Hummell et al. 2016) utilises PCA

[1] EU-27 + 5: 27 Member States (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden), and the five associated countries (Iceland, Liechtenstein, Norway, Switzerland and UK).

and aggregates the extracted components with equal weighting to characterise the social vulnerability in Brazil, considering indicators such as percentage of females, the ratio of female and male mean-monthly-income, share of population employed in the extractive industry, proportion of population that either completed middle school, or have incomplete high school level. Similarly, Aksha et al. (2019) adapted the SoVI to the Nepal case using 39 variables, e.g. percentages of females, absentee population, population employed in agriculture, forestry, fishing, mining and quarrying. Furthermore, Tasnuva et al. (2021) analysed SoVI in a municipality of Bangladesh using PCA at household level through 33 indicators obtained from surveys and the results indicate that high population density, poor economic condition, the presence of vulnerable groups, unstable income generating sources, unplanned urban and poor infrastructure, lack of services and lack of adequate sewage systems are the key drivers of social vulnerability in the study area.

Similarly, the Social Vulnerability Index (SVI) developed at the US Center for Disease Control (Flanagan et al. 2011), or the Strength-based Social Vulnerability Index (SSVI) proposed by Ogie and Pradhan (2019), provides a composite index of vulnerability. Vulnerability has a direct connection among social and economic stratification (Myers et al. 2008), therefore, quantifying those inequalities allows a better understanding of it. For instance, there are some key variables or indicators that must be considered to measure those inequalities, such as access to any kind of service, lack of legislation, building age conditions, age and gender, among others.

In turn, Harlan et al. (2013) provided different indicators by also applying PCA with statistically weighted factors, to prove that aspects such as population over the age of 65, old dependency, Latino immigrants and others, are highly relevant to heatwave vulnerability. Furthermore, Conlon et al. (2020) demonstrated the sensitivity of the heat vulnerability index, also generated using PCA with equally weighted factors, although to input variables such as population over the age of 65, early leavers from education and training, distance to waterbodies, etc. Moreover, Yu et al. (2021) used PCA to create an aggregated Drought Vulnerability Index (DVI), to then calculate a Drought Hazard Index (DHI), using a wide range of indicators to reach vulnerability (population, cultivated areas, water use for paddy area, water use for cultivated area, industrial water use or penetration rate, among others). Moreover, the risk of extreme heat in Hong Kong (Hua et al. 2021) has also been analysed by integrating indicators of daily and night-time temperature, population density and a PCA analysis of socio-demographic characteristics such as population age, economic status or housing characteristics.

Regarding vulnerability to floods, Fekete (2009) applies the PCA technique for Germany to obtain vulnerability at the county level and then validates the results by comparing them with a real case event. He uses 50 indicators, such as population over 65 years old, hospital beds, graduates without basic education, university students, new residents and GDP per labour force. Moreover, Bashier Abbas et al. (2014) utilised a composite vulnerability index based on the combination of indicators using an alternative technique to PCA. They provide 9 indicators for measuring flood vulnerability (family, gender, education, house materials, etc.), and 11 indicators for health vulnerability (healthcare services impacted by previous floods, water source, walking time to the nearest health facility, etc.). Liu and Li (2016) employ a combination of PCA and expert scoring to analyse the social vulnerability of rural households to flood hazards in mountainous regions. In Jamshed et al. (2020), the weighted average technique is applied to construct an index of rural vulnerability to floods, where two indices are calculated, one for holistic vulnerability and another for livelihood vulnerability, using the same indicators. In the same direction, Wu (2021) employed PCA with equally weighted factors to analyse coastal floods in Connecticut providing 30 indicators, whereas Kotzee and Reyers (2016) employed PCA for 23 variables to analyse flood vulnerability, which enables adaptation to specific contexts. In contrast, Zhang et al. (2018) combined Data Envelopment Analysis (DEA), correlation coefficient analysis and PCA with statistically weighted factors, using a wide range of variables such as the proportion of R&D funds, number of patents granted, number of people with tertiary level education and GDP per capita, among others. Finally, Martins and Nunes (2020) analyse flash flood risk perception using categorical principal components analysis (CATPCA)—a variant of PCA—providing 16 variables.

On the other hand, some authors consider other types of hazards, such as Finch et al. (2010) or Myers et al. (2008), who analyse vulnerability to hurricanes. The first (Finch et al. 2010) used PCA with equally weighted factors, which defined the underlying, independent and dominant components of social vulnerability, showing 74.8% of the variance in the original input. In addition, they use a deductive index with ordinary least squares (OLS) regression and 29 variables. The second (Myers et al. 2008) analyse demographic, social and economic data using 24 variables at the county level, first employing PCA to reduce the initial 24 variables to 5 factors, followed by an OLS and spatial regression to estimate the post-storm migration.

Other authors also use PCA combined with other techniques to analyse vulnerability. It is the case of Frigerio and De Amicis (2016) who combine it with cluster analysis, making use of a wide range of indicators: unemployment ratio, population over the age of 65, foreign residents and dependency ratio, among others. Navarro et al. (2020) also make use of the same combination, specifically k-means, to obtain a vulnerability index based on 14 socioeconomic and demographic indicators. Furthermore, Tate et al. (2016) analysed flood social vulnerability with PCA using 12 indicators, providing a new approach for indicator weights, based on the results of meta-analysis, so that each indicator has relative importance based on case study findings. Additionally, Rufat et al. (2013, 2019) developed the social vulnerability profiles (SVP) which also combines PCA with cluster analysis, to produce spatially compact vulnerability profiles instead of a single aggregated value, resulting in an index with 36 indicators, including age-dependent (under 5 and over 65), median age, unemployed, female, etc. In turn, Barros et al. (2015) analysed the territorial vulnerability to tsunami impact, building a composite index consisting of morphological, structural building, and social and taxable property vulnerability components, combining different weighting and aggregation approaches (such as PCA for social vulnerability, or an evaluation matrix for structural building vulnerability). Finally, Maletta and Mendicino (2020) analyse vulnerability in terms of people and road characteristics, combining a PCA methodology for individual attributes with a geo-processing approach for road aspects.

3 Methodology

3.1 Indicators and data sources

The assessment includes a set of indicators which considers multiple dimensions such as demography, education and research, economy, environment, social capital and perception, health, gender and governance. This selection of indicators is based on literature review and data availability, and they are grouped into two different categories: susceptibility and coping capacity, being the first those which increase the territorial

Table 1 Indicators for territorial vulnerability assessment

Code	Dimension	Indicator	Description
DEM_MEDAGEPOP	Demography	Age of population	Median age of population
DEM_YOUNGDEP	Demography	Young-age dependency	Ratio between population aged 0–14 years to 15–64
DEM_OLDDEP	Demography	Old dependency	Ratio between population aged 65 years and over to 15–64
EDU_EARLYLEAV	Education and research	Early leavers from education and training	Percentage of those aged 18–24 with at lowest secondary education
ECO_RISKPOVERTY	Economy	Risk of poverty and social exclusion	Percentage of people at risk of poverty or social exclusion
ECO_PRIMSECT	Economy	Primary sector employments	Percentage of people employed in agriculture, forestry or fishing
ECO_UNEMPRATE	Economy	Unemployment rate	Rate of unemployed people between 20 and 64 years old
ENV_IRRIGAT	Environment	Irrigable and irrigated areas	Share of irrigable and irrigated areas in utilised agricultural area
DEM_NATGROWRT	Demography	Natural population change	Crude rate of natural change of population
DEM_CNMIGRATRT	Demography	Migration rate	Crude rate of net migration plus statistical adjustment
EDU_TERTEDC	Education and research	Tertiary educational attainment	Tertiary educational attainment of population between 25 and 64 years old
EDU_RDEXPEN	Education and research	R&D expenditure	Research and development expenditure as percentage of GDP
EDU_RDPERS	Education and research	R&D personnel and researchers	Research and development personnel and researchers as percentage of total employment
EDU_PATENTS	Education and research	Patent applications to the EPO	Patent applications to the European Patent Office (EPO) per million inhabitants
SCP_SOCIALCAPITAL	Social capital and perception	Social capital	Social capital as a combination of social trust, social support and participation
SCP_RISKPERCEPTION	Social capital and perception	Risk perception	Aggregated value of perception of droughts and floods importance, perception of climate change importance, and budget prioritisation by population for climate change and environmental protection
HEA_HOSPIBEDS	Health	Hospital beds	Number of hospital beds per 100 000 inhabitants
HEA_PHYSICIANS	Health	Practising physicians	Physicians or medical doctors per 100 000 inhabitants

Table 1 (continued)

Code	Dimension	Indicator	Description
ECO_GDP	Economy	GDP per inhabitant	Gross Domestic Product (GDP) per inhabitant
ECO_PROFSECT	Economy	Professional, scientific and technical employments	Percentage of professional, scientific and technical jobs
ENV_SDGI	Environment	Spatial distribution of GI	Spatial distribution of Green Infrastructure (GI)
ENV_POTENGI	Environment	Potential GI network for CC&DRR policies	Potential Green Infrastructure (GI) network serving the purposes of climate change (CC) and disaster risk reduction (DRR) policies
GEN_EQUALITYINDEX	Gender	Gender equality index	Index developed by the European Institute for Gender Equality (EIGE) that considers work, money, knowledge, time, power and health domains
GOV_QGI	Governance	Quality of Government index	This index focuses on both perceptions and experiences with public sector corruption, along with the extent to which citizens believe various public sector services are impartially allocated and of good quality in the EU
GOV_SIGCM	Governance	Municipalities signatories to the Covenant of Mayors	Weighted share of municipalities that have signed the Covenant of Mayors and have also submitted an action plan

vulnerability, while the second decrease it. Table 1 shows a brief description of the 25 indicators analysed, among which 8 support susceptibility evaluation, and 17 support coping capacity assessment.

Regarding the susceptibility:

- Young and elderly individuals are considered more susceptible to damage during the occurrence of a natural hazard than the adult population due to their health sensitivity and reduced mobility (Finch et al. 2010; Yoon 2012; Chen et al. 2013; Harlan et al. 2013; Bashier Abbas et al. 2014; Frigerio and Amicis 2016; Liu and Li 2016; Kotzee and Reyers 2016; Aksha et al. 2019; Rufat et al. 2019; Maletta and Mendicino 2020; Navarro et al. 2020; Medina et al. 2020; Yu et al. 2021).
- In relation to the population with low socioeconomic status, those with low education level, unemployed or at risk of poverty and social exclusion, are also considered more vulnerable due to their fragile source of income and limited access to resources (Blaikie et al. 1994; Cutter et al. 2003; Brooks et al. 2005; Myers et al. 2008; Schmidtlein et al. 2008; Fekete 2009; Finch et al. 2010; Yoon 2012; Chen et al. 2013; Harlan et al. 2013; Bashier Abbas et al. 2014; de Loyola Hummell et al. 2016; Frigerio and Amicis 2016; Karagiorgos et al. 2016; Tate et al. 2016; Barreca et al. 2017; Zhang et al. 2018; Aksha et al. 2019; Rufat et al. 2019; Conlon et al. 2020; Maletta and Mendicino 2020; Medina et al. 2020; Navarro et al. 2020; Wu 2021).
- Additionally, territories with a high share of irrigated agriculture, as well as those with high presence of primary sector employment, i.e. agriculture, forestry and fishing, are vulnerable to natural hazards because those activities are highly dependent on climate and environment (Brooks et al. 2005; Schmidtlein et al. 2008; Finch et al. 2010; Yoon 2012; Chen et al. 2013; Harlan et al. 2013; de Loyola Hummell et al. 2016; Zhang et al. 2018; Aksha et al. 2019; Wu 2021).

Regarding coping capacity:

- Demographic growth indicates the attractiveness of the region (de Loyola Hummell et al. 2016; Aksha et al. 2019).
- A high level of education and research through tertiary educational attainment, research and development expenditure, and personnel, researchers and patent applications indicate a higher capacity to produce knowledge and develop innovative solutions to new problems (Brooks et al. 2005; Zhang et al. 2018; Medina et al. 2020).
- Social capital captures the level of cohesion, trust and access to resources based on social networks; the higher the social capital is, the lower the vulnerability (Pelling 1998; Wisner 2003; Nakagawa and Shaw 2004; Newman and Dale 2005; Murphy 2007; Myers et al. 2008; Morrow 2008; Varda et al. 2009; Ainuddin and Routray 2012).
- Risk perception is a sociocultural phenomenon affected by social organisation and values, which guides the behaviour of people in prevention and response actions related to natural hazards; generally speaking, the higher the risk perception the lower the vulnerability (Douglas and Wildavsky 1982; Grothmann and Reusswig 2006; Oliver-Smith 1996; Wachinger et al. 2013; Birkholz et al. 2014; Martins and Nunes 2020; Medina et al. 2020; Wu 2021).
- The health system is also an important indicator of the capacity to respond to a disaster; in this case, indicators referring to the number of hospital beds and practising physicians are considered (Cutter et al. 2003; Myers et al. 2008; Fekete 2009; Finch et al. 2010; Yoon 2012; Chen et al. 2013; Zhang et al. 2018; Maletta and Mendicino 2020).

- The economic capacity of a territory has a strong influence on the number of resources that may be mobilised to implement mitigation actions and to facilitate the recovery process after a disaster (Cutter et al. 2003; Brooks et al. 2005; Myers et al. 2008; Zhang et al. 2018; Rufat et al. 2019).
- The environment also plays an important role in the capacity of a territory to cope with disasters, so indicators of the spatial distribution of existing and potential green infrastructure networks, that contribute to climate change and disaster risk reduction policies have been included (Meerow and Newell 2017).
- The impacts of disasters are not evenly distributed in society; when there is a high level of inequality among social groups, the impacts are higher. It is also true in the case of gender inequality, which has been captured with the gender equality index (Bashier Abbas et al. 2014; Jamshed et al. 2020; Martins and Nunes 2020; Medina et al. 2020).
- Finally, an important aspect of the coping capacity of a territory is the governance dimension, which influences the effectiveness of the implementation of disaster risk reduction policies, included in the assessment through the quality of government index and the percentage of municipalities signatories to the Covenant of Mayors (Brooks et al. 2005; Kotzee and Reyers 2016; Medina et al. 2020).

Information regarding the sources and scale of the presented indicators is included as supplementary information. The main source is EUROSTAT, although some indicators from previous ESPON projects and EIGE (European Institute for Gender Equality) have also been considered. All the indicators are available in the ESPON Database Portal.[2]

3.2 Vulnerability assessment

The methodology to assess vulnerability is based on multivariate statistical techniques, specifically PCA, which is widely used in vulnerability assessments, as presented previously.

The process to perform the evaluation of vulnerability to natural hazards is as follows: (i) development of a data model; (ii) data gathering and pre-processing of indicators; (iii) management of missing values; (iv) definition of weights of vulnerability factors; (v) combination of vulnerability factors; and (vi) geographical representation. Steps one, two, three and six are original and specific to this research, step four is based on Cutter et al. (2003) and Nardo et al. (2008), and step five is based on Tapia et al. (2017).

The *first step* consists of the development of a data model for vulnerability assessment based on a literature review and data availability, considering the susceptibility and coping capacity categories. The selection of the reference year has been a balance between the use of the most recent data possible and the years in which the greatest number of indicators were covered.

In the *second step*, the data from different sources were downloaded, filtered and cleaned. The datasets whose source is EUROSTAT have been downloaded through the SDMX API using the EUROSTAT package (Lahti et al. 2017) in R language. All the indicators are considered in relative terms, i.e. divided by population, area or GDP, to allow comparison between areas of different extents. In some cases, the indicator had to be constructed from sub-variables. That is the case, for instance, of the social capital indicator, which was calculated based on specific responses of the Special Eurobarometer '223 Social Capital' related to social trust,

[2] ESPON Database Portal. Available at: https://www.espon.eu/espon-database

support and participation. Additionally, the indicator of risk perception was calculated through the responses to the questions about droughts and floods, climate change and opinions about budget prioritisation in risk-related topics from the Special Eurobarometer '501 Attitudes of European citizens towards the Environment' and from the Standard Eurobarometer. As supplementary information, a table with details regarding the pre-processing and management of the missing values by indicator is included.

The *third step* is related to the management of the missing values. Some of the indicators (see table 'pre-processing and missing values management' in supplementary information) are not fully available for all the units of analysis, which requires a data policy to fill them. The analysis was performed from highest to lowest resolution, i.e. if there was any missing value at NUTS3, then we searched for the same information at NUTS2 to complete it, and so on until NUTS0. If there were still any missing data, the value was filled with the median value of the distribution.

The *fourth step* refers to the weight of the vulnerability factors. In this step, the indicators for susceptibility and coping capacity were processed separately, so that the autocorrelation of the variables could be analysed. Then, indicators were grouped into factors in the direction of maximum variance using PCA, producing a model with a reduced number of dimensions. The number of factors was decided based on the criteria proposed by Nardo et al. (2008), respecting the following sequence: number of factors with eigenvalues over one, number of factors with an individual contribution to overall variance over 10%, and number of factors with a cumulative contribution to overall variance over 60%. To simplify the interpretation, the matrix of factor loadings was transformed using a varimax rotation. The varimax rotation minimises the number of variables that load high on a single factor, thereby increasing the percentage variation between each factor (Cutter et al. 2003).

After the rotated matrix was obtained, the weight of the indicators was calculated following the methodology by Nardo et al. (2008). First, the square root of the loadings was calculated, and then, those values were divided by the proportion of variance explained by each factor to obtain the weighted intra-factor loadings. Subsequently, the cross-factor weighted loadings were calculated by dividing intra-factor weighted loads by the proportion of variance explained by each factor in relation to the total variance explained by all selected factors. Finally, those individual indicators with the highest factor loadings across all factors are selected and rescaled. This approach minimises the possible redundancy due to the considered indicators.

It is worth mentioning a limitation of PCA vulnerability studies in that the results are relative and therefore valid only within the sample analysed. For this reason, the levels of vulnerability are not comparable with other regions outside the study area.

During the *fifth step*—combination of vulnerability factors–the final vulnerability indices were obtained by NUTS3. First, the susceptibility and coping capacity scorings were calculated using a geometric aggregation (Tapia et al. 2017) as shown in Eqs. (1 and 2).

$$\mathrm{SU}_t = \prod\nolimits_i^I \mathrm{su}_t^{w_i} \tag{1}$$

where SU_t = susceptibility score for territory t; su = value of susceptibility factor i for territory t; and w_i weight of susceptibility factor i.

$$\mathrm{CC}_t = \prod\nolimits_i^I \mathrm{cc}_t^{w_i} \tag{2}$$

where CC_t = coping capacity score for territory t; cc = value of coping capacity factor i and territory t; and w_i weight of coping capacity factor i.

Subsequently, the vulnerability score was obtained using Eq. (3) by dividing susceptibility by coping capacity after rescaling them.

$$V_t = \frac{\mathrm{SU}'_t}{\mathrm{CC}'_t} \tag{3}$$

where V_t = vulnerability score for territory t; SU'_t = rescaled susceptibility score for territory t; CC'_t = rescaled coping capacity for territory t.

Finally, the *sixth and last step* was geographical representation. In this step, the resulting matrix of the vulnerability results was joined to the spatial features, and the final maps were generated. For the representation, we opt for ranking the vulnerability using the natural breaks algorithm, which seeks to minimise the variance within categories, while maximising the variance between categories. The geographical representation is useful to interpret the existing vulnerability spatial patterns.

3.3 Approach for vulnerability and economic impacts relation

The analysis of the vulnerability related to the distribution of the economic impacts due to natural hazards is complex due to the holistic consideration of vulnerability, and the multiple effects that it may have, on disaster management: preparation before it occurs, the distribution of the impacts when it happens, and the reconstruction process after having gone through it. Moreover, the way the impact is measured may differ significantly, e.g. fatalities, people affected and economic impacts.

Considering the widely accepted framework of analysis, where risk is the result of combining hazard, exposure and vulnerability, and limiting risk to the purely economic dimension, we can assume that risk, measured in economic terms, will be the result of the aggregation of the different hazards that can affect a territory, the exposure calculated as GDP of each of them, and their vulnerability, which was obtained in the previous assessment. Therefore, understanding the risk as economic losses, the approach to validate the vulnerability assessment in this analysis is to evaluate how well the hazard, exposure and vulnerability components are able to explain past economic impacts. For that purpose, the outputs from the evaluation of aggregated natural hazards (Klein et al. this issue) and past economic impacts (Petsinaris et al. this issue) of the ESPON-TITAN project are combined with the present vulnerability assessment carried out.

For this purpose, a multiple regression model was defined with economic impacts as the dependent variable and hazard exposure and vulnerability as the independent variables as shown in Eq. (4). The logarithm transformation is applied because the past economic impacts and GVA are skewed distributions. Then, the results are analysed to check whether the residuals present spatial autocorrelation issues using the Global Moran I statistic. In such a case, the assumption of independence of the residuals is violated, making the multiple regression model to be discarded.

$$\log(\mathrm{IMP}) = H + \log(\mathrm{GVA}) + V \tag{4}$$

where log(IMP) = the logarithm of the total past economic impacts; H = the aggregated hazard; log(GVA) = logarithm of Gross Value Added; and V = territorial vulnerability.

This issue was solved with the use of a spatial regression model, which is a type of regression model where the structure and values of the neighbourhood are considered (LeSage 2008; Fischer and Wang 2011), using the R package spatialreg (Bivand et al.

Table 2 Factor loadings after varimax rotation for susceptibility

Indicator	FC1	FC2	FC3	FC4	FC5	FC6
DEM_MEDAGEPOP	0,034	0,639	−0,018	0,026	−0,202	−0,005
DEM_YOUNGDEP	−0,023	0,012	−0,027	0,032	0,948	0,025
DEM_OLDDEP	−0,038	0,766	0,000	−0,004	0,134	0,018
EDU_EARLYLEAV	0,037	0,006	0,033	0,963	0,031	−0,035
ECO_RISKPOVERTY	−0,553	−0,064	−0,200	0,236	−0,182	0,219
ECO_PRIMSECT	0,034	0,008	0,030	−0,034	0,025	0,968
ECO_UNEMPRATE	−0,829	0,034	0,101	−0,117	0,084	−0,111
ENV_IRRIGAT	−0,030	−0,005	0,973	0,031	−0,025	0,029

2021). According to the package documentation, the model fitting functions include maximum likelihood methods. The evaluation of the relative quality concerning the multiple regression model was performed using the Akaike Information Criterion (AIC) estimator, and its explanatory capacity was calculated using the Nagelkerke pseudo-R squared.

4 Results

4.1 Susceptibility

The indicators are analysed using PCA and six factors are obtained using the criteria described in the methodology section, i.e. the number of factors with eigenvalues over one, the number of factors with an individual contribution to overall variance over 10%, and the number of factors with a cumulative contribution to overall variance over 60%. Table 2 shows the loadings of the indicators for the obtained factors after a varimax rotation. The first factor shows a high correlation between the risk of poverty and the unemployment rate. In the same way, the second factor shows a high correlation between the median age of the population and old dependency. Finally, factors three to six explain one indicator each.

To obtain the weighting of the indicators, first, the square of the factor loadings was calculated after varimax rotation; in the sequence, the indicators with the highest factor loadings were grouped into intermediate composite indicators; then, those intermediate indicators were aggregated based on the proportion of variance explained; after that, the weights were computed according to the factor loadings across all factors; finally, the susceptibility values were obtained using the geometric aggregation of the indicators with the correspondent weights. Figure 1 shows the susceptibility to natural hazards at NUTS3.

The spatial distribution of susceptibility to natural hazards shows visible hotspots in Spain, southern Italy, Greece, Romania and Bulgaria. If coping capacity is not taken into account, we could say that the most susceptible territories are more likely to suffer damage during the occurrence of an extreme natural event.

4.2 Coping capacity

As with susceptibility, the selected indicators are analysed using PCA, obtaining the most significant factors using the criteria previously described. Table 3 shows the loadings of

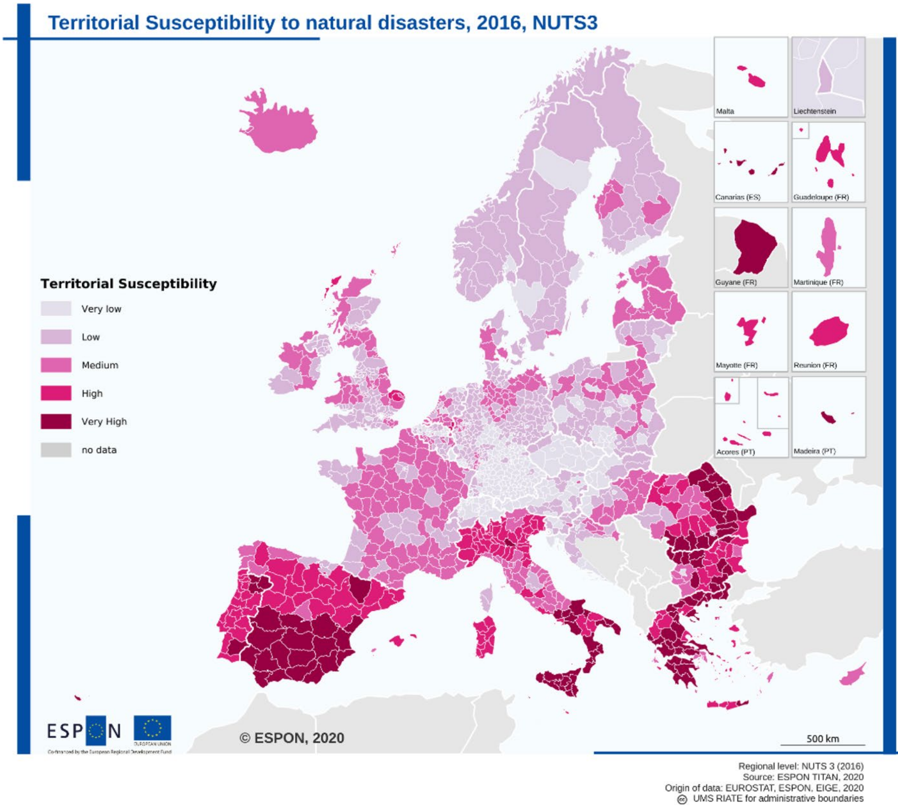


Fig. 1 Susceptibility to natural hazards

the indicators of coping capacity for the first six factors out of the fourteen obtained after a varimax rotation (see supplementary information for all factor loadings). The first factor shows a high correlation between social capital, gender equality index and quality of government. In addition, the second factor shows a high correlation between research and development expenditure, hospital beds and quality of government. Finally, the remaining indicators explain one indicator each.

The indicator weighting was performed using the factor loadings table after varimax rotation. The square factor loadings were calculated; then, these values were divided by the proportion of variance explained by each factor, and subsequently, intra-factor weighted loads were divided by the proportion of variance explained by each factor in relation to the total cumulative variance; then, the weight of the indicators was computed based on the factor loadings across all factors; finally, the geometric aggregation of the indicators was calculated. The coping capacity to natural hazards at NUTS3 is shown in Fig. 2.

The territories identified with lower coping capacity to natural hazards are located mostly in Baltic countries and Eastern Europe countries, i.e. Estonia, Latvia, Lithuania, Bulgaria, Romania, Hungary, Czech Republic and Poland. A low coping capacity means that a territory may face greater challenges to deal successfully with different stages of the disaster management cycle—before, during and after it occurs.

Table 3 Factor loadings after varimax rotation for coping capacity: first six factors (see supplementary information for full table)

Indicator	FC1	FC2	FC3	FC4	FC5	FC6
DEM_NATGROWRT	−0,004	−0,007	0,002	0,001	0,999	−0,001
DEM_CNMIGRATRT	−0,004	−0,011	−0,001	0,001	−0,001	−0,004
EDU_TERTEDC	0,006	0,020	0,015	0,005	0,002	−0,005
EDU_RDEXPEN	0,250	0,374	0,003	0,008	0,022	−0,022
EDU_RDPERS	−0,062	−0,095	0,000	−0,005	−0,008	0,016
EDU_PATENTS	0,000	−0,001	−0,001	0,000	0,000	−0,002
SCP_SOCIALCAPITAL	0,697	−0,139	0,146	0,015	−0,011	0,065
SCP_RISKPERCEPTION	−0,035	−0,045	0,033	0,007	−0,005	0,003
HEA_HOSPIBEDS	−0,111	0,836	0,037	0,010	−0,015	−0,012
HEA_PHYSICIANS	0,022	0,019	0,971	−0,004	0,002	−0,010
ECO_GDP	0,004	0,009	0,004	0,002	0,001	−0,005
ECO_PROFSECT	0,001	−0,003	−0,007	−0,001	0,000	−0,001
ENV_SDGI	0,003	0,000	−0,005	−0,001	0,000	−0,002
ENV_POTENGI	0,003	0,005	−0,004	0,999	0,001	0,001
GEN_EQUALITYINDEX	0,555	−0,067	−0,144	−0,001	−0,008	−0,127
GOV_QGI	0,354	0,354	−0,108	−0,041	0,023	0,074
GOV_SIGCM	−0,004	0,006	0,009	−0,001	0,001	−0,987

4.3 Vulnerability

The vulnerability was calculated by combining susceptibility and coping capacity by dividing the susceptibility by the coping capacity, and the resulting score was normalised between 1 and 2. To classify the vulnerability levels, the natural breaks algorithm was used, obtaining 288 territories with high or very high vulnerability. Figure 3 shows the spatial territorial vulnerability pattern in relative terms for 2016 and at NUTS3.

By the spatial distribution, it can be seen that eastern and southern territories are more vulnerable to natural hazards, with special mention of some regions in Hungary, Romania, Bulgaria, Greece, Italy, Spain and Portugal. Nevertheless, some regions in Estonia, Latvia, Lithuania, Poland, France and the Czech Republic are also significantly vulnerable.

The most vulnerable territories have a high susceptibility, as shown by indicators of early leavers from education, unemployment rate and the risk of poverty, and a reduced coping capacity, as shown by indicators of research and development personnel and expenditure, patent applications, gross domestic product, professional and technical employment, social capital, gender equality index and quality of governance.

4.4 Vulnerability and economic impacts relation

To perform the analysis of how vulnerability and the past economic impacts due to natural hazards are related, we assume that the consequence of disasters may be understood and explained by those past economic impacts, which are based on a combination of hazard, exposure and vulnerability. For that, a model has been developed considering

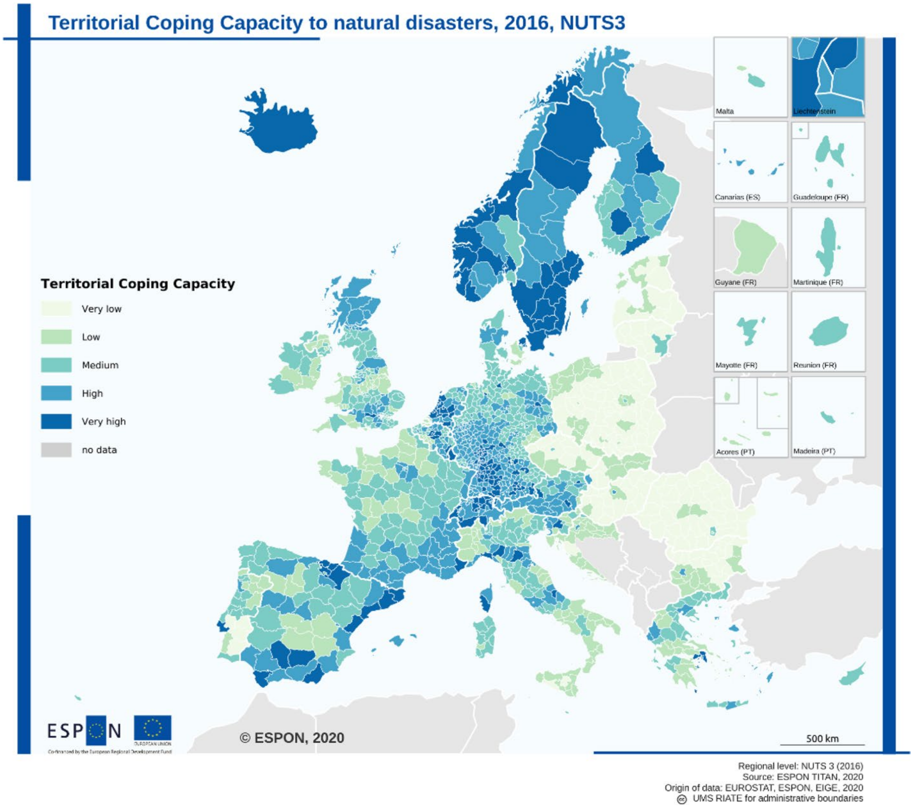


Fig. 2 Coping capacity to natural hazards

the aggregated hazards analysed in ESPON-TITAN (Klein et al. this issue), the GVA as a measure of exposure and the vulnerability obtained in this study.

The distribution of economic impacts is unbalanced, presenting some regions with high values and a large number with very low values. Different combinations have been tested, and the best way to explain the highest values was by performing a logarithmic transformation of the economic impacts and the GVA (Eq. 4). If logarithmic transformation were not performed, the residuals of the model would increase systematically as the values of the economic impacts increase.

First, a multiple linear regression model was fitted using Eq. (4), and the spatial distribution of the residuals was verified. For this purpose, Moran I of residuals was calculated and returned a score of 0.59, indicating the existence of spatial autocorrelation and therefore violating the principle of residuals being randomly distributed, which confirms the relevance of performing a spatial regression.

Afterwards, the mentioned formula was used in a spatial regression model, i.e. having as independent variables the mean hazard, the log of the GVA and the vulnerability, and as the dependent variable, the log of the total past economic impacts (Eq. 4). The p value of the three independent variables is less than 0.05, which means that there is a statistically significant relationship with the response variable in the model. The

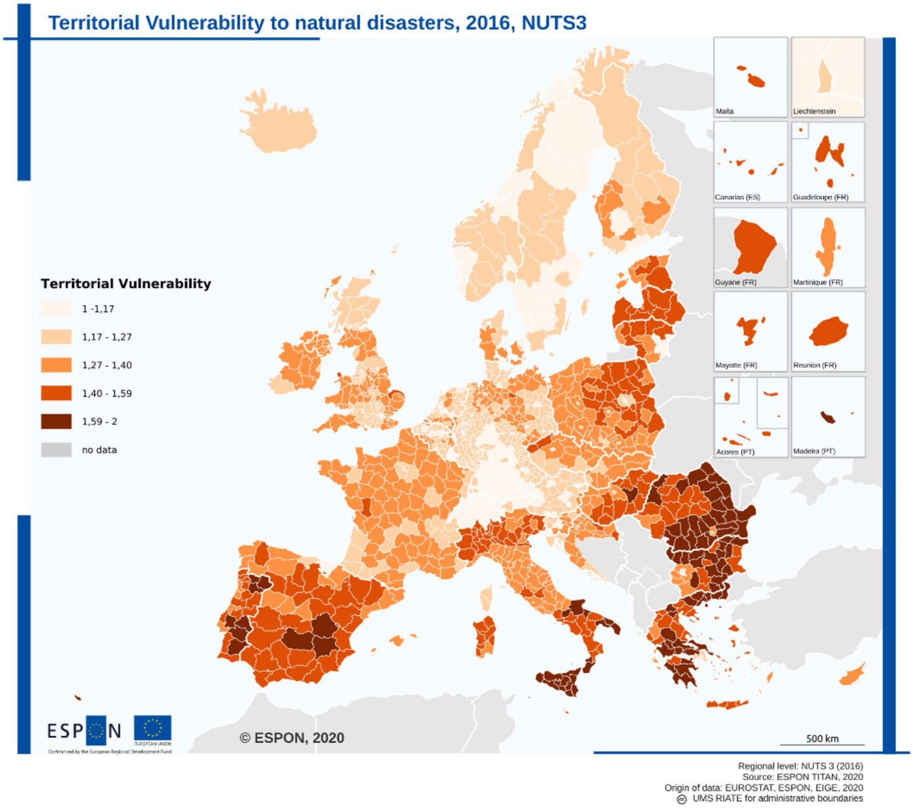


Fig. 3 Territorial vulnerability to natural hazards

coefficient of the vulnerability variable is positive, thus indicating a positive relationship between vulnerability and economic impacts.

Furthermore, the potential systematic change in the spread of the residuals is also analysed. In Fig. 4, the residuals versus fitted, and the normal Q–Q plots, indicate a homoscedasticity behaviour of the residuals, which means that they are equally distributed. Finally, regarding the goodness of fit, a Nagelkerke pseudo-R-squared of 0.75 is obtained, which can be considered a relatively good fit.

In sum, the comparison between the spatial distribution of past economic impacts (Fig. 5a) and the predicted economic impacts obtained by the spatial regression model (Fig. 5b) shows relatively good agreement.

5 Discussion

The results of the analysis of the vulnerability to natural hazards show a spatial distribution where Eastern Europe, Southern Europe and the Baltic Region outstand. It is noteworthy that the application of different methodologies and the definition of the set of indicators may lead to different outcomes, which reinforces the importance of an accurate selection of both. The consideration of PCA as a widely employed methodology in the study of

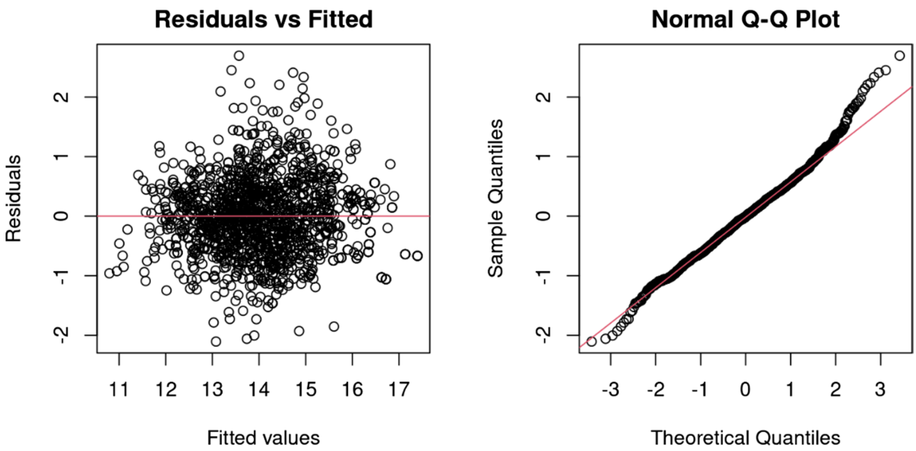
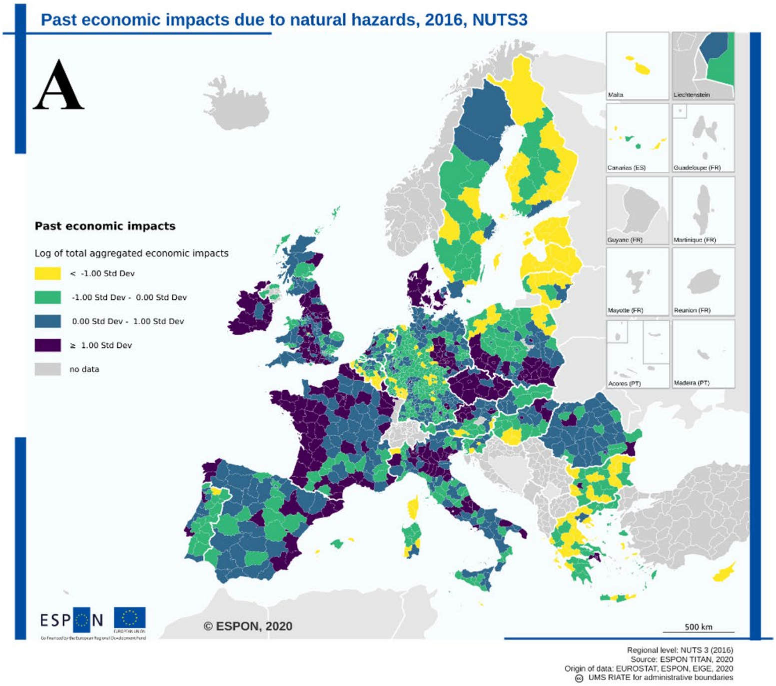


Fig. 4 Residuals versus fitted and normal Q–Q plots

vulnerability to natural hazards, and the selection of indicators supported by an extensive literature review to characterise susceptibility and coping capacity, have been a key starting point for this research to ensure the consistency of the results.

Regarding the use of the PCA, the criteria chosen are the same as those proposed by Nardo et al. (2008). These criteria are rather conservative, in the sense that they tend to produce a high number of factors for the indicators analysed. In the susceptibility case, eight indicators are reduced to six factors, with the first two factors being the only ones that explain more than one indicator. The first factor shows a high correlation between the risk of poverty and the unemployment rate, which could indicate economically depressed areas. Moreover, the second factor shows a high correlation between the median age of the population and old dependency, which is understood as a factor of population ageing. On the other hand, in the coping capacity case, seventeen indicators are explained by fourteen factors, with the first two factors explaining three indicators each, and the remaining factors explaining one indicator each. The first factor relates social capital, gender equality and quality of government, i.e. a factor related to a high level of development and social equity. The second coping capacity factor shows a high correlation between research and development expenditure, hospital beds and quality of government, which could be called a factor of a high level of technical development. Although the criterion used has been widely used and is widely cited, it is worth mentioning that there is a trade-off between the number of factors obtained and the variance explained, and that therefore a less conservative criterion would produce a simpler model with less factors at the expense of explaining a larger amount of cumulative variance. Another important fact worth noting is that the results of the evaluation are relative in nature as a consequence of the methodology; therefore, values had to be interpreted in comparative terms between the 1395 NUTS3 analysed, which implies that the character of very high or low vulnerability is related to the complete sample analysed and cannot be directly compared with other regions outside the study area.

In terms of data, it is worth mentioning some constraints related to the lack of information due to the scale and geographical coverage of the analysis. Data management at the NUTS3 level for 32 countries has been a challenge during the collection and pre-processing of the indicators. In total, approximately 34,500 single values were analysed as a result of considering 1395 NUTS3 regions and 25 indicators. This is a typical burden in this kind



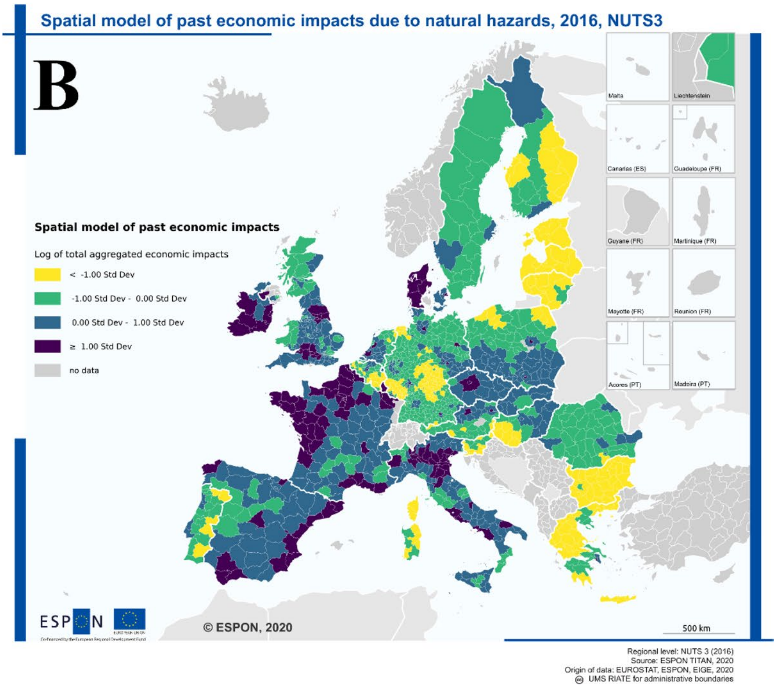


Fig. 5 **a** Past economic impacts due to natural hazards. **b** Spatial regression model of past economic impacts

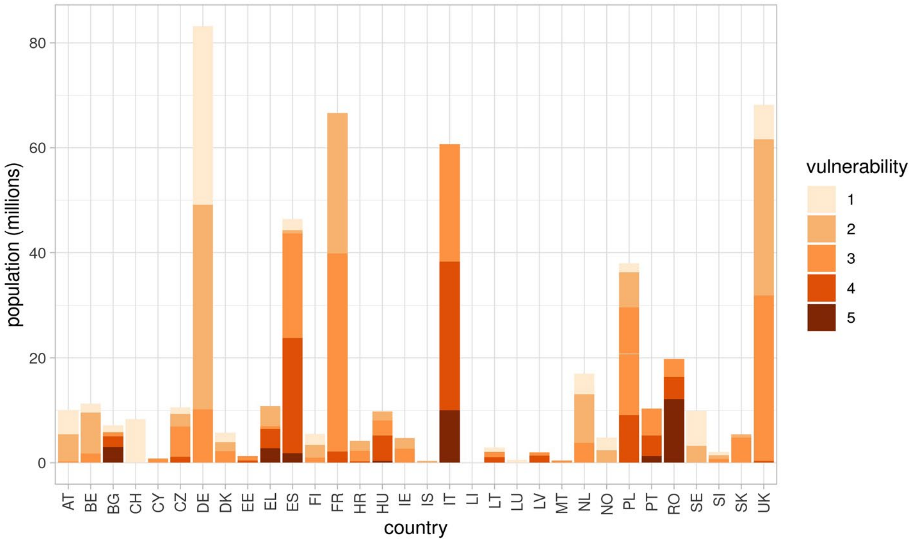


Fig. 6 Population living in vulnerable territories

of analysis, resulting in significant time and effort consumption for the preparation of the material to be used in the research. To minimise the effects of working with that exhaustive amount of data, a systematic approach for missing value management had to be designed. In summary, whenever a missing value was found for a given region, specific datasets at a higher scale were downloaded to fill them. Nevertheless, some datasets were available only at NUTS2, NUTS1 or NUTS0 level, limitation that should be considered in the interpretation of the results. An additional constraint regarding data was the geographical coverage and completeness of indicators in different geographical areas; in general, data from EU countries were easier to obtain than from EFTA countries. This is possible due to the strong common data-sharing strategies and technology available in the first group compared to the second.

In relation to the relevance of the results, one key outcome was evidencing the population living in vulnerable territories in order to adequately reflect the calculated vulnerability. Figure 6 shows the population as of 2016 in each vulnerability level by country. The population living in territories with high or very high vulnerability is 20% of the total sample, i.e. 116 out of 528 million inhabitants. Romania, Italy, Bulgaria and Greece are the countries with more population in highly vulnerable territories, followed by Spain, Portugal, Hungary, Poland and France.

Another revealing way to better understand the result is to visualise the population living in vulnerable territories as a percentage of the total population of the country (Fig. 7). The countries with the highest share of the population living in very high vulnerable territories are Romania, Bulgaria, Greece and Italy, while the countries with the highest share of the population living in high or very high vulnerable territories are Romania, Bulgaria, Latvia, Italy and Greece.

Finally, due to the subject matter and the geographical scope of the study, it is pertinent to compare the results with the ESPON NATURAL HAZARDS project (ESPON 2006), which also analysed the vulnerability to natural hazards for all ESPON countries at NUTS3 level using an indicator-based methodology. In that project, the approach was to

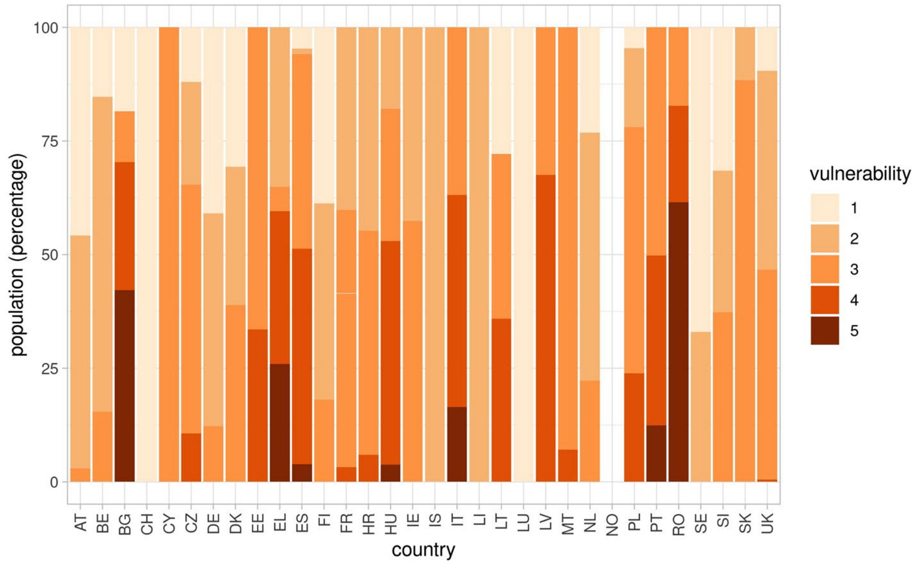


Fig. 7 Population living in vulnerable territories as a percentage of the population of the country

conceptualise risk as the combination of two components—hazard and vulnerability—thus not considering the third–exposure—as is currently broadly conceptualised by the international community (IPCC 2022; UNDRR 2022). Vulnerability was composed by the damage potential and the capacity to cope, and characterised by four indicators, three of them for damage potential (regional GDP per capita, population density and proportion of fragmented natural areas), and one for coping capacity (the national GDP). Furthermore, the indicators were aggregated using expert criteria, where the weights of the indicators were decided to be 10% for fragmented areas and 30% for the remaining ones. Differently than the mentioned approach, in this research risk is based on the latest conceptual framework by UNDRR (2022) and IPCC (2022), and so includes exposure as a component of risk. In the first, the density of the population is part of vulnerability component, whereas the present analysis considers it to be an exposure indicator. As a consequence of the update of the methodological approach, the total number of indicators now is significantly higher, 25 over 4. In order to be able to aggregate these 25 indicators, a PCA was performed, technique which is usually chosen for vulnerability analysis. Other important difference is that the database was updated with the latest information available. In terms of vulnerability results, the spatial distribution in the previous project shows that more populated urban areas were more vulnerable, due to the higher income concentration and population density, which is again potentially related to exposure more than with vulnerability. As a result of the conceptualisation of vulnerability, which is more in line with current approaches, and the use of more up-to-date data, the results obtained can be considered as an update of the vulnerability analysis with respect to the previous project.

The objectives pursued in this research, and as a consequence also the methodology used, were framed by the ESPON-TITAN project, which has geographical coverage and thematic scope defined as a starting point of the research. The combination of three different results (hazard analysis, economic impacts of disasters and vulnerability assessment) was performed to find the relations and better understand a limited number of natural hazards and the territorial patterns of related disasters, also predefined. The extension in the scope of this research may bring new inputs that could refine and improve the results, although the present products are already robust enough to fulfil the goal of the project by contributing to deepening the knowledge about the patterns of territorial vulnerability to natural hazards in Europe at NUTS3 level, allowing to capture the multiple dimensions involved and characterise more precisely the susceptibility and coping capacity, hence vulnerability.

6 Conclusions

Vulnerability matters. The level of vulnerability of a territory contributes to the understanding of why the occurrence of a natural hazard might become a disaster. High correlation between vulnerability scoring and past economic impacts of natural disasters could imply that decreasing the levels of vulnerability in a territory may directly contribute to reducing the risk of disaster (Greiving and Navarro, this issue). The applied methodology assessing and combining hazards, impacts and vulnerability definitively provides added value for analysis and decision-making at different territorial scales for disaster risk management, in first instance.

The assessment of the territorial vulnerability according to the methodology used in this research shows that the most vulnerable territories to disasters are located in Eastern Europe, Southern Europe and the Baltic Region. This pronounced territorial pattern of vulnerability implies an uneven distribution biased towards traditionally less developed territories. In addition, the analysis of the population living in vulnerable territories and its share of the total (corresponding to 20%) offers valuable information to highlight specific cases that deserve special attention.

Although vulnerability to natural hazards is the result of multiple complex dimensions and therefore difficult to tackle, the indicator-based approach provides a suitable proxy for assessing vulnerability, proven by previous studies and, particularly as presented, concerning the economic impacts due to natural hazards. In this research the vulnerability assessment was done applying PCA, which has been conducted holistically and does not exclusively consider the economic impacts of disasters. Besides, the spatial regression model was fundamental to confirm that the resulting vulnerability distribution and territorial pattern is fairly good to explain past economic impacts due to natural hazards.

Despite the finding are revealing when showing pronounce territorial patterns and useful for regional benchmarking across ESPON countries, the results should be interpreted considering the methodology applied and certain limitations which were not possible to overcome given the scope of the analysis and some contextual conditions (i.e. relative nature of the results in relation to the sample of regions analysed, specific datasets granularity, as well as data coverage when dealing with heterogeneous country statistics).

Being like that, future research could explore this relation between territorial indicators of vulnerability and the economic impacts of disasters by combining quantitative risk assessments with indicator-based vulnerability ones. For example, damage curves could be used to estimate the economic cost of floods combined with different indicators of territorial vulnerability to analyse the economic impacts of past disasters. In this way, the analysis by indicator would potentially show the most influential ones in explaining the economic impacts of disasters caused by natural hazards.

In sum, knowledge of territorial vulnerability patterns is crucial for developing not only proper disaster risk management policies but also climate change adaptation plans (Blecking et al. this issue). It allows the orientation of policies towards the most vulnerable regions, prioritising those most affected by the occurrence and consequences of an extreme natural phenomenon. Additionally, from a single region perspective, serves as a first screening for prioritising certain hazards and vulnerabilities which would require deeper analysis and understanding through targeted research for placed based regional or local policies. In this sense, territorial planning and disaster risk management have a key role, since their implementation is closely linked to several components of vulnerability. In conclusion, fine place-based decision-making in this field has the potential to correct certain existing inequalities between territories, that basically is the final objective of multiple European territorial policies.

Furthermore, in terms of economic impact, a clearer focus on vulnerability reduction results to be an effective way to reduce the effects of potential disasters, as shown by the relation between territorial vulnerability and economic impacts.

All these findings are definitively helping to advance in bridging disaster risk management and climate change adaptation, following a clear tendency started in the IPCC AR6 (IPCC 2022) followed by European policies as the 2021 EU Adaptation Strategy and initiatives like the EU Climate Mission.

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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