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ESPON-TITAN
Territorial Impacts
of Natural Disasters

Applied research

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Vulnerability Analysis

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ESPON-TITAN
Territorial Impacts of Natural Disasters

Table of contents

LIST OF MAPS ..... **II**

LIST OF FIGURES ..... **III**

LIST OF TABLES ..... **IV**

ABBREVIATIONS ..... **V**

1 INTRODUCTION **1**

2 METHODOLOGY **4**

2.1 DESCRIPTION OF THE INDICATORS AND DATA SOURCES 4
2.2 METHODS FOR VULNERABILITY ASSESSMENT 8
2.3 APPROACH FOR VULNERABILITY VALIDATION 12

3 RESULTS **13**

3.1 SUSCEPTIBILITY 13
3.2 COPING CAPACITY 15
3.3 VULNERABILITY 17
3.4 POPULATION IN VULNERABLE TERRITORIES 18
3.5 VALIDATION OF VULNERABILITY ASSESSMENT 20

4 DISCUSSION AND CONCLUSIONS **23**

4.1 DATA CONSTRAINTS 23
4.2 CLUSTERS OF PAST ECONOMIC IMPACTS AND TERRITORIAL VULNERABILITY 23
4.3 COMPARISON WITH VULNERABILITY DISTRIBUTION FROM ESPON CLIMATE PROJECT 24
4.4 CONCLUSIONS 25

REFERENCES **26**

List of Maps

Map 3.1 Susceptibility to natural hazards, 2016, NUTS3 14
Map 3.2 Coping capacity to natural hazards, 2016, NUTS3 17
Map 3.3 Territorial vulnerability to natural hazards, 2016, NUTS3 18
Map 3.4 Past economic impacts due to natural hazards, 2016 21
Map 3.5 Spatial model of past economic impacts due to natural hazards, 2016 22
Map 4.1 Relation between past economic impacts and territorial vulnerability 24

List of Figures

Figure 1.1 Risk components according to UNDRR ... 1
Figure 1.2 Core concepts of IPCC Fifth Assessment Report ... 2
Figure 3.1 Distribution of susceptibility indicators ... 13
Figure 3.2 Distribution of coping capacity indicators ... 15
Figure 3.3 Population living in vulnerable territories ... 19
Figure 3.4 Population living in vulnerable territories in percentage of population of country .. 19

List of Tables

Table 2.1 Indicators for territorial vulnerability assessment 4
Table 2.2 Source and scale of indicators 7
Table 2.3 Pre-processing and missing values... 9
Table 3.1 Factor loadings after varimax rotation for susceptibility 13
Table 3.2 Factor loadings after varimax rotation for coping capacity...................................... 16

Abbreviations

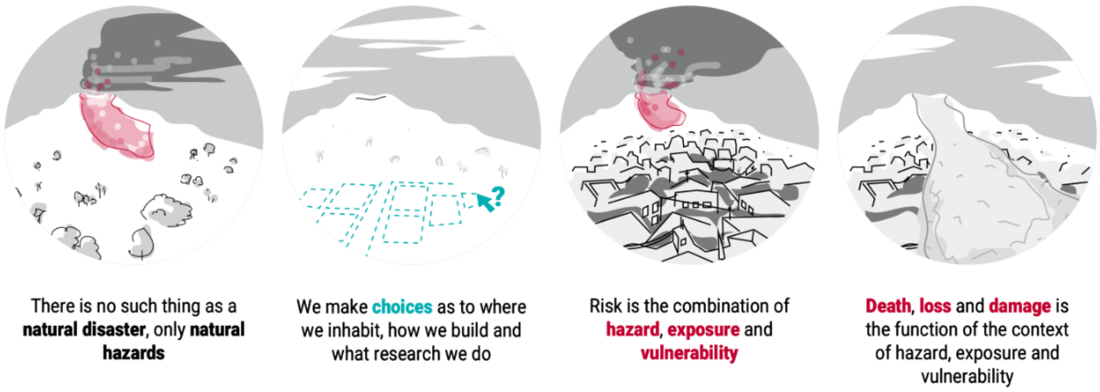
CPI	Consumer Price Index
CRED	Centre for Research on the Epidemiology of Disasters
EAA	European Economic Area
EC	European Commission
ECB	European Central Bank
ECU	European Currency Unit
EDO	European Drought Observatory (JRC)
EFAS	European Flood Awareness System
ELSUS	European Landslide Susceptibility
ESDAC	European Soil Data Centre
ESPON	European Territorial Observatory Network
ESPON EGTC	ESPON European Grouping of Territorial Cooperation
EU	European Union
GCM	Global Climate Model
GDO	Global Drought Observatory
GloFAS	Global Flood Awareness System
HANZE	Historical Analysis of Natural Hazards in Europe
HICP	Harmonized Index of Consumer Prices
JRC	Joint Research Centre
NATECHS	Natural-technical hazards
NUTS	Nomenclature of Territorial Units for Statistics
PGA	Peak ground acceleration
RCM	Regional Climate Model
SHARE	Seismic Hazard Harmonization in Europe project
SPI	Standardized Precipitation Index
WISC	Windstorm Information Service
WMS	Web Map Service

1 Introduction

This annex describes the territorial vulnerability assessment developed in the context of the ESPON-TITAN “Territorial Impacts of Natural Disasters” project.

The approach of the vulnerability assessment follows the one proposed by the Disaster Risk Management and Climate Change communities which are compatible in terms of the components of risk. For UNDRR (2019), vulnerability is a component of risk along with hazard and exposure (Figure 1.1).

Figure 1.1 Risk components according to UNDRR



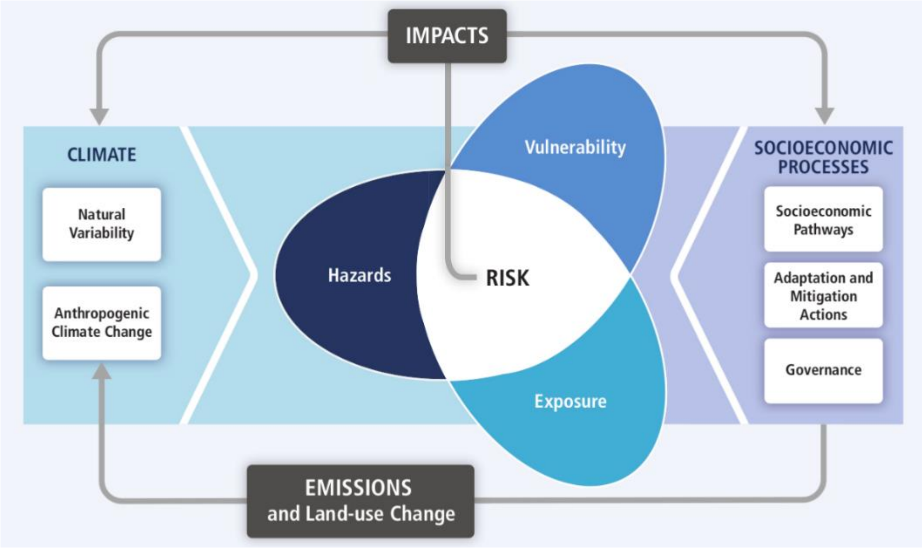
Source: UNDRR (2019)

From the Climate Change community perspective, the approach to vulnerability has become increasingly compatible with that of disaster risk management, especially since the publication of “Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation“ (IPCC, 2012) and “Fifth Assessment Report of the Intergovernmental Panel on Climate Change“ (IPCC, 2014) of the Working Group II. The Figure 1.2 shows the core components of this approach, where the risk depends on the hazard, exposure and vulnerability levels.

Therefore, both for IPCC and UNDRR the risk is divided into hazard, exposure and vulnerability. If any of these components is not present, then there will be no risk of disaster. Let’s consider for instance a territory with a medium level of hazard and exposure, but a very low level of vulnerability, then the risk will be low. Moreover, in a territory with medium level of hazard and vulnerability, but very low level of exposure, then the risk will be also low. Therefore, it should be noted that vulnerability must be combined with hazard and exposure in order to assess disaster risk.

The vulnerability concept captures the fact that comparable levels of hazard and exposure produce different levels of impact in different territories. The impacts of natural hazards are unevenly distributed across space.

Figure 1.2 Core concepts of IPCC Fifth Assessment Report



Source: IPCC, 2014

The territorial vulnerability to natural hazards is understood as the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of a territory to the impacts of hazards (adapted from UN (2016).

The concept of vulnerability is complex and encompasses multiple dimensions which requires a holistic and integrative approach (Blaikie et al., 1994; Birkmann, 2013). In this regard, the assessment has considered the following dimensions: demography, education and research, economy, environment, social capital, risk perception, gender and governance. The indicators included are divided in those that increase the territorial vulnerability i.e. susceptibility, and those that decrease it, i.e. coping capacity. The indicators considered, based on literature review and data availability, aim to capture the complexity involved in the triggering of a disaster on the occurrence of a natural hazard.

The scale of analysis is NUTS3 level and the geographic coverage includes the following 32 countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom.

The methodology for the territorial vulnerability assessment is described in the second chapter of this report. That section includes the description of the indicators and data sources, the methodology for vulnerability assessment and the approach for vulnerability validation.

The third chapter shows the territorial vulnerability results. It includes the results of territorial susceptibility, coping capacity and vulnerability, population living in vulnerable territories and the validation of the vulnerability assessment.

Finally, the discussion and conclusions chapter highlight the data constraints found in the assessment, clusters of past economic impacts and territorial vulnerability, a comparison with previous projects, and a final conclusions section.

2 Methodology

2.1 Description of the indicators and data sources

The assessment has included a set of indicators based on literature review and data availability (Blaikie et al., 1994; Cutter et al., 2003; Karagiorgos et al., 2016). They are grouped in two categories, susceptibility and coping capacity (Table 2.1). The susceptibility indicators increase the territorial vulnerability, while those of coping capacity decrease it. The table below shows the 25 indicators analysed, 8 for susceptibility and 17 for coping capacity, along with a description of them.

The indicators included consider multiple dimensions like demography, education and research, economy, environment, social capital and perception, health, gender and governance.

Table 2.1 Indicators for territorial vulnerability assessment

	Code	**Dimension**	**Indicator**	**Description**
susceptibility	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 20-64 years old
	ENV_IRRIGAT	Environment	Irrigable and irrigated areas	Share of irrigable and irrigated areas in utilised agricultural area
coping capacity	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 25-64 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

	Code	Dimension	Indicator	Description
	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 prioritization 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
	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 CC and 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 Majors	Weighted share of municipalities that have signed the Covenant of Majors and have also submitted an Action Plan

In the first category of indicators, the young and old population is more susceptible to damage during the occurrence of a natural hazard than the adult population due to health sensitivity and reduced mobility. The population with low socio-economic status, those with low education level, unemployed or at risk of poverty and social exclusion, are also more vulnerable due to its fragile source of income and limited access to resources (Blaikie et al., 1994; Cutter et al., 2003; Karagiorgos et al., 2016). Additionally, territories with 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.

Regarding coping capacity, the demographic growth indicates the attractiveness of the region. A high level in 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. The social capital captures the level of cohesion, trust and access to resources based on the social networks, the higher the social capital, the lower the vulnerability (Pelling, 1998; Wisner, 2003; Nakagawa and Shaw, 2004; Newman and Dale, 2005; Murphy, 2007; Morrow, 2008; Varda et al., 2009; Ainuddin and Routray, 2012). Risk perception is a sociocultural phenomenon affected by social organization 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). The health system is also an important indicator of the capacity to respond to a disaster, in this case the indicators of number of hospital beds and practising physicians are considered. The economic capacity of a territory has a strong influence in the amount of resources that may be mobilised to implement mitigation actions and to facilitate the recovery process after a disaster. The environment also plays an important role in the capacity of a territory to cope with disasters, specifically the indicators of spatial distribution of green infrastructure and the potential green infrastructure network serving the purposes of climate change and disaster risk reduction policies have been included. The impacts of disasters are not evenly distributed in the society, when there is a high level of inequality among social groups the impacts of disasters are higher to them, this also occurs in the case of gender inequality which has been captured with the gender equality index. Finally, an important aspect in the coping capacity of a territory is the governance dimension which influences in 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 Majors.

Table 2.2 shows the source and scale of the indicators included in the assessment. The source of most of them is EUROSTAT, but indicators from previous ESPON projects and from EIGE (European Institute for Gender Equality) have been also included.

Table 2.2 Source and scale of indicators

	Indicator	Source	Scale
susceptibility	DEM_MEDAGEPOP	EUROSTAT	NUTS3
	DEM_YOUNGDEP	EUROSTAT	NUTS3
	DEM_OLDDEP	EUROSTAT	NUTS3
	EDU_EARLYLEAV	EUROSTAT	NUTS2
	ECO_RISKPOVERTY	EUROSTAT	NUTS2
	ECO_PRIMSECT	EUROSTAT	NUTS3
	ECO_UNEMPRATE	EUROSTAT	NUTS2
	ENV_IRRIGAT	EUROSTAT	NUTS2
coping capacity	DEM_NATGROWRT	EUROSTAT	NUTS3
	DEM_CNMIGRATRT	EUROSTAT	NUTS3
	EDU_TERTEDC	EUROSTAT	NUTS2
	EDU_RDEXPEN	EUROSTAT	NUTS2
	EDU_RDPERS	EUROSTAT	NUTS2
	EDU_PATENTS	EUROSTAT	NUTS3
	SCP_SOCIALCAPITAL	EUROSTAT	NUTS0
	SCP_RISKPERCEPTION	EUROSTAT	NUTS0
	HEA_HOSPIBEDS	EUROSTAT	NUTS2
	HEA_PHYSICIANS	EUROSTAT	NUTS2
	ECO_GDP	EUROSTAT	NUTS3
	ECO_PROFSECT	EUROSTAT	NUTS3
	ENV_SDGI	ESPON	NUTS3/2
	ENV_POTENGI	ESPON	NUTS3/2
	GEN_EQUALITYINDEX	EIGE	NUTS0
	GOV_QGI	ESPON	NUTS2
	GOV_SIGCM	ESPON	NUTS2

2.2 Methods for vulnerability assessment

The methodology to obtain the vulnerability is based on multivariate statistical techniques, specifically principal component analysis (PCA), which is widely used in vulnerability assessments (Cutter et al., 2003; Fekete, 2009; Tapia et al., 2017).

The steps to obtain the vulnerability to natural hazards have been the following:

1. Development of a data model.
2. Pre-processing of indicators.
3. Missing values management.
4. Weight of vulnerability factors.
5. Combination of vulnerability factors.
6. Geographic representation.

The first step consists in the development of a data model for the vulnerability assessment based on the previously mentioned approach which considers the susceptibility and coping capacity. The selection of the indicators is done based on literature review and data availability. 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 pre-processing of indicators step the data is downloaded, filtered and clean from different sources. The datasets which source is EUROSTAT have been downloaded through the SDMX API using R language EUROSTAT package (Lahti et al., 2017). All the indicators are in relative terms, i.e. divided by population, area, or GDP to allow comparison between areas of different size. In some cases, the indicator itself needs to be constructed from sub-variables. That is the case, for instance, for social capital indicator which is calculated with specific responses of the Special Eurobarometer '223 Social Capital' related to social trust, support, and participation. Also, for the indicator of risk perception which is calculated through the responses to the questions about droughts and floods, climate change and opinion about budget prioritization in risk related topics from the Special Eurobarometer '501 Attitudes of European citizens towards the Environment' and from the Standard Eurobarometer.

The third step is missing values management. Some of the indicators are not fully available for all the units of analysis which requires a policy to fill them. The approach has been to begin with highest resolution available dataset, i.e. NUTS3, and in case a value is missing, retrieve a new dataset of lower resolution, e.g. NUTS2, and fill it with the new value if available, in the case the data is still unavailable go to lower resolution, e.g. NUTS1, and repeat the process until NUTS0. In the case, there are still missing values which were filled with the median value of the distribution.

In Table 2.3, a description of the steps taken is provided for each indicator, in regard to both pre-processing and missing values.

Table 2.3 Pre-processing and missing values

Indicator	**Pre-processing and missing values management**
DEM_MEDAGEPOP	The data has been retrieved from EUROSTAT at NUTS3 level and scaled between 1 and 2
DEM_YOUNGDEP	The data has been retrieved from EUROSTAT at NUTS3 level and scaled between 1 and 2
DEM_OLDDEP	The data has been retrieved from EUROSTAT at NUTS3 level and scaled between 1 and 2
EDU_EARLYLEAV	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ECO_RISKPOVERTY	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ECO_PRIMSECT	The data has been retrieved from EUROSTAT at NUTS3 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ECO_UNEMPRATE	The data has been retrieved from EUROSTAT at NUTS2 level, if any value is missing it is filled with median value, and it is finally scaled between 1 and 2
ENV_IRRIGAT	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
DEM_NATGROWRT	The data has been retrieved from EUROSTAT at NUTS3 level, if any value is missing it is filled with median value, and it is finally scaled between 1 and 2
DEM_CNMIGRATRT	The data has been retrieved from EUROSTAT at NUTS3 level, if any value is missing it is filled with median value, and it is finally scaled between 1 and 2
EDU_TERTEDC	The data has been retrieved from EUROSTAT at NUTS2 level, if any value is missing it is filled with median value, and it is finally scaled between 1 and 2
EDU_RDEXPEN	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS1 level data, and the with NUTS0 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
EDU_RDPERS	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS1 level data, and the with NUTS0 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
EDU_PATENTS	The data has been retrieved from EUROSTAT at NUTS3 level, missing values are firstly filled with NUTS1 level data, and the with NUTS0 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
SCP_SOCIALCAPITAL	The indicator is calculated using the Special Eurobarometer '223 Social Capital' answers to the questions related to social trust, social support and social participation

Indicator	Pre-processing and missing values management
SCP_RISKPERCEPTION	The indicator is calculated using the Special Eurobarometer '501 Attitudes of European citizens towards the Environment' and from the Standard Eurobarometer answers to the questions related to perception of droughts and floods importance, perception of climate change importance, and budget prioritization by population for climate change and environmental protection
HEA_HOSPIBEDS	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
HEA_PHYSICIANS	The data has been retrieved from EUROSTAT at NUTS2 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ECO_GDP	The data has been retrieved from EUROSTAT at NUTS3 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ECO_PROFSECT	The data has been retrieved from EUROSTAT at NUTS3 level, missing values are firstly filled with NUTS0 level data, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ENV_SDGI	The data has been retrieved from ESPON at NUTS3/2 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
ENV_POTENGI	The data has been retrieved from ESPON at NUTS3/2 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
GEN_EQUALITYINDEX	The data has been retrieved from EIGE at NUTS0 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
GOV_QGI	The data has been retrieved from ESPON at NUTS2 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2
GOV_SIGCM	The data has been retrieved from ESPON at NUTS2 level, if any value is still missing it is filled with median value, and it is finally scaled between 1 and 2

The fourth step is the weight of vulnerability factors. In this step the indicators are processed using Principal Component Analysis (PCA) separately for susceptibility and coping capacity. This statistical technique analyses the autocorrelation of the variables and it allows grouping the indicators into factors in the direction of maximum variance producing a model with a reduce number of dimensions. The number factors is decided based on the criteria proposed by Nardo et al. (2008): (i) number of factors with eigenvalues lager than one; (ii) number of factors with individual contribution to overall variance by more than 10%; (iii) number of factors with cumulative contribution to overall variance by more than 60%. In order to simplify the interpretation, the matrix of factor loadings is transformed using Varimax rotation.

After the rotated matrix is obtained, the weight of the indicators is calculated in following manner: firstly, the square root of the loadings is calculated; then those values are divided by the proportion of variance explained by each factor to obtain the weighted intra-factor loadings; subsequently, across-factor weighted loadings are calculated by dividing intra-factor weighted loads by the proportion of variance explained by each factor in relation to total variance explained by all selected factors; finally, those individual indicators with the highest factor loadings across all factors are selected and rescale. This approach minimizes the possible redundancy due to the considered indicators.

During the combination of vulnerability factors step the NUTS3 regions obtain the final vulnerability indices (Tapia et al., 2017). Firstly, the susceptibility and coping capacity scoring is calculated using a geometric aggregation as shown in equations 1 and 2.

$$SU_t = \prod_i^I su_t^{w_i} \qquad (1)$$

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.

$$CC_t = \prod_i^I cc_t^{w_i} \qquad (2)$$

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 is obtained using the following equation by dividing between susceptibility and coping capacity after re-scaling them.

$$V_t = \frac{SU'_t}{CC'_t} \qquad (3)$$

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

Finally, the last step is the geographic representation. In this step, the vulnerability results obtained in tabular format from previous steps are joined the spatial geometries and cartographic results are generated. The ranking of vulnerability levels has been established using the natural breaks algorithm, which seeks to minimize the variance within categories, while maximizing the variance between categories. The geographic representation serves to interpret the existing vulnerability spatial patterns and present the results.

2.3 Approach for vulnerability validation

An important issue regarding any territorial assessment is the validation of the results. The approach to validate the vulnerability assessment in this analysis have been, understanding the risk as economic losses, 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 natural hazards (see Annex 1) and past economic impacts (see Annex 2) from ESPON-TITAN are combined with the vulnerability assessment.

For this purpose, a multiple regression model is defined being the dependent variable the economic impacts and the independent variables the hazard, the exposure and the vulnerability. Then, the results are analysed to check whether the residuals present spatial autocorrelation issues using Global Moran I statistic. In such a case, the assumption of independence of the residuals is violated which makes the multiple regression model to be discarded.

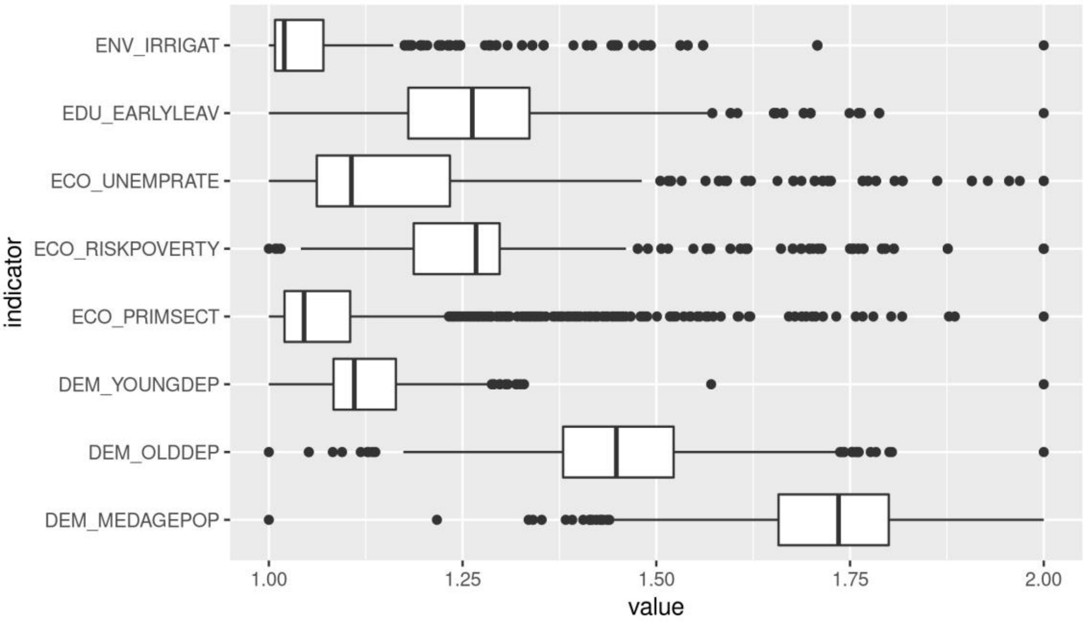
To solve this issue, a spatial regression model is used (LeSage, 2008; Fischer and Wang, 2011). A spatial regression model is a type of regression model where the structure and values of the neighbourhood is taken into account. The evaluation of the relative quality of the model respect to the multiple regression model is performed using the Akaike information criterion (AIC) estimator and its explanatory capacity using the Nagelkerke pseudo R squared.

3 Results

3.1 Susceptibility

The Figure 3.1 visually shows the median, first and third quartiles, interquartile range and outliers for each of the indicators used for the susceptibility analysis.

Figure 3.1 Distribution of susceptibility indicators



The indicators are analysed using PCA and the first 6 factors are kept using the criteria described in the methodology section. The following table (Table 3.1) shows the loadings of the indicators for the first four factors after a varimax rotation. The first factor shows, for example, high correlation between positive young-age dependency and negative risk poverty, primary sector employment and unemployment rate. In the same way, the second factor shows a high correlation between positive median age of population, positive old dependency and negative young-age dependency.

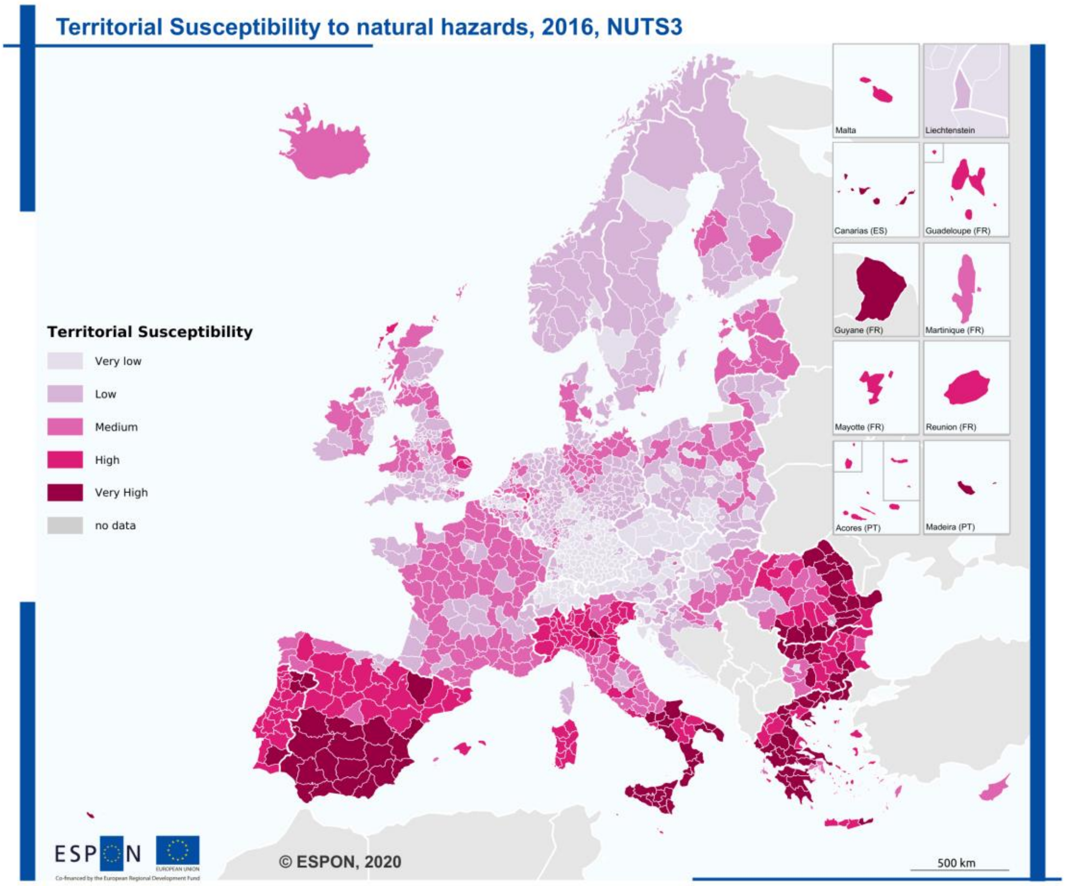
Table 3.1 Factor loadings after varimax rotation for susceptibility

Indicator	**PC1**	**PC2**	**PC3**	**PC4**
DEM_MEDAGEPOP	0,019	0,655	-0,006	0,050
DEM_YOUNGDEP	0,292	-0,448	0,069	0,291
DEM_OLDDEP	0,103	0,595	0,087	0,139
EDU_EARLYLEAV	0,004	0,038	-0,045	0,893
ECO_RISKPOVERTY	-0,548	-0,031	0,084	0,272
ECO_PRIMSECT	-0,728	-0,012	-0,088	-0,099
ECO_UNEMPRATE	-0,244	-0,101	0,568	0,071
ENV_IRRIGAT	0,114	0,054	0,805	-0,08

To obtain the indicators weighting the procedure described in methodology section is performed (Nardo et al., 2008; Tapia et al., 2017): firstly the square of the factor loadings is calculated after varimax rotation; the indicators with highest factor loadings are grouped into intermediate composite indicators; then those intermediate indicators are aggregated based on the proportion of variance explained; subsequently, the weights are computed according to the factor loadings across all factors; finally, the susceptibility is obtained using the geometric aggregation of the indicators with the obtained weights.

The Map 3.1 shows the susceptibility to natural hazards at NUTS3 level obtained after the calculation following the described procedure.

Map 3.1 Susceptibility to natural hazards, 2016, NUTS3



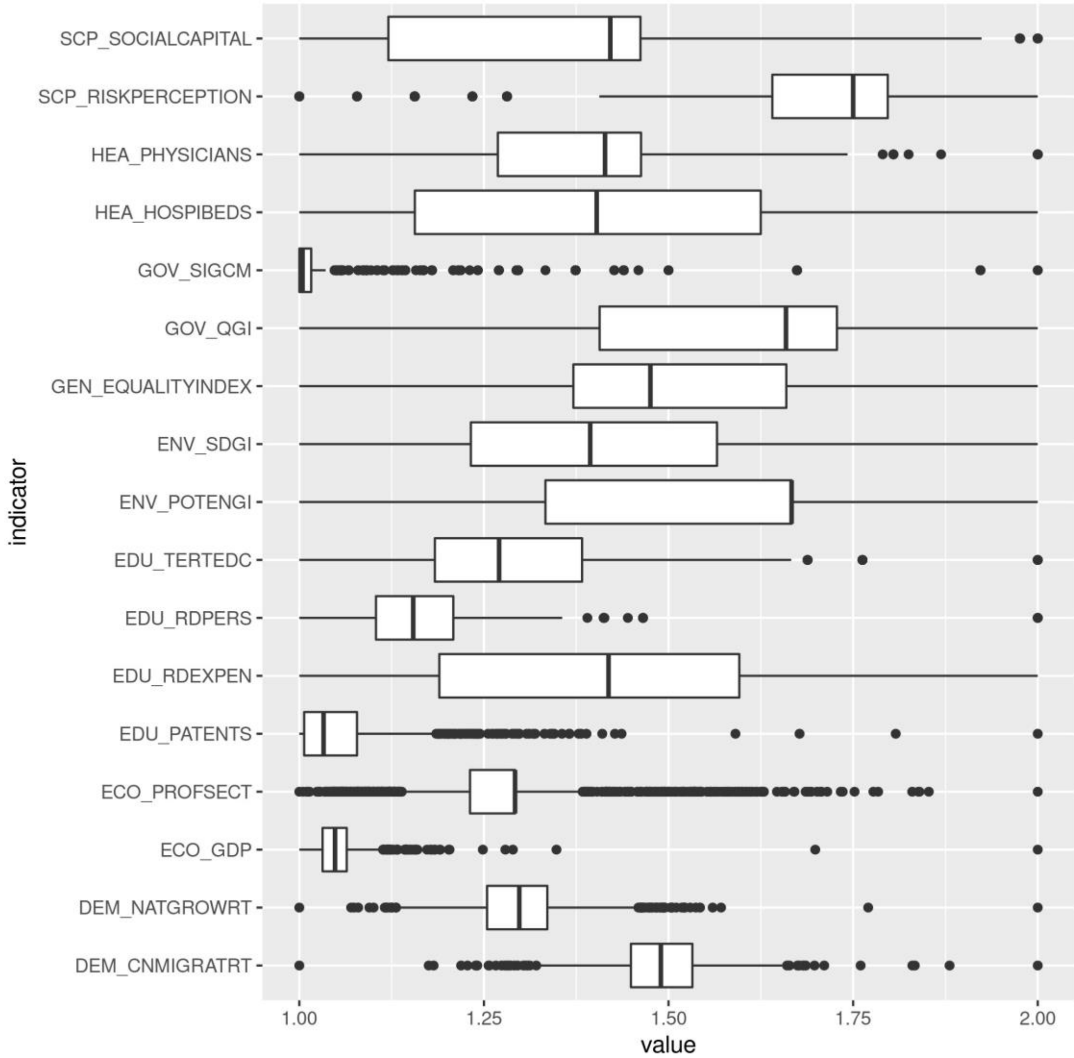
Regional level: NUTS 3 (2016)
Source: ESPON TITAN, 2020
Origin of data: EUROSTAT, ESPON, EIGE, 2020
© UMS RIATE for administrative boundaries

The spatial distribution of susceptibility to natural hazards shows some hotspots in Spain, southern Italy, Greece, Romania and Bulgaria. Without considering any other factors, the most susceptible territories are more likely to suffer damage during the occurrence of an extreme natural event.

3.2 Coping capacity

As with susceptibility, the Figure 3.2 visually shows the median, first and third quartiles, inter-quartile range and outliers for each of the indicators used for the coping capacity analysis.

Figure 3.2 Distribution of coping capacity indicators



The indicators are analysed using PCA, obtaining 14 factors using the criteria described in the methodology. The following table (Table 3.2) shows the loadings of the indicators of coping capacity for the first four factors after a varimax rotation. For instance, the first factor shows a high correlation between positive social capital, risk perception, technical employment, gender equality and quality of government. Besides, the second factor shows a high correlation between positive research and development expenditure, patent applications, hospital beds, quality of government, and negative risk perception and negative signatories to the Covenant of Majors.

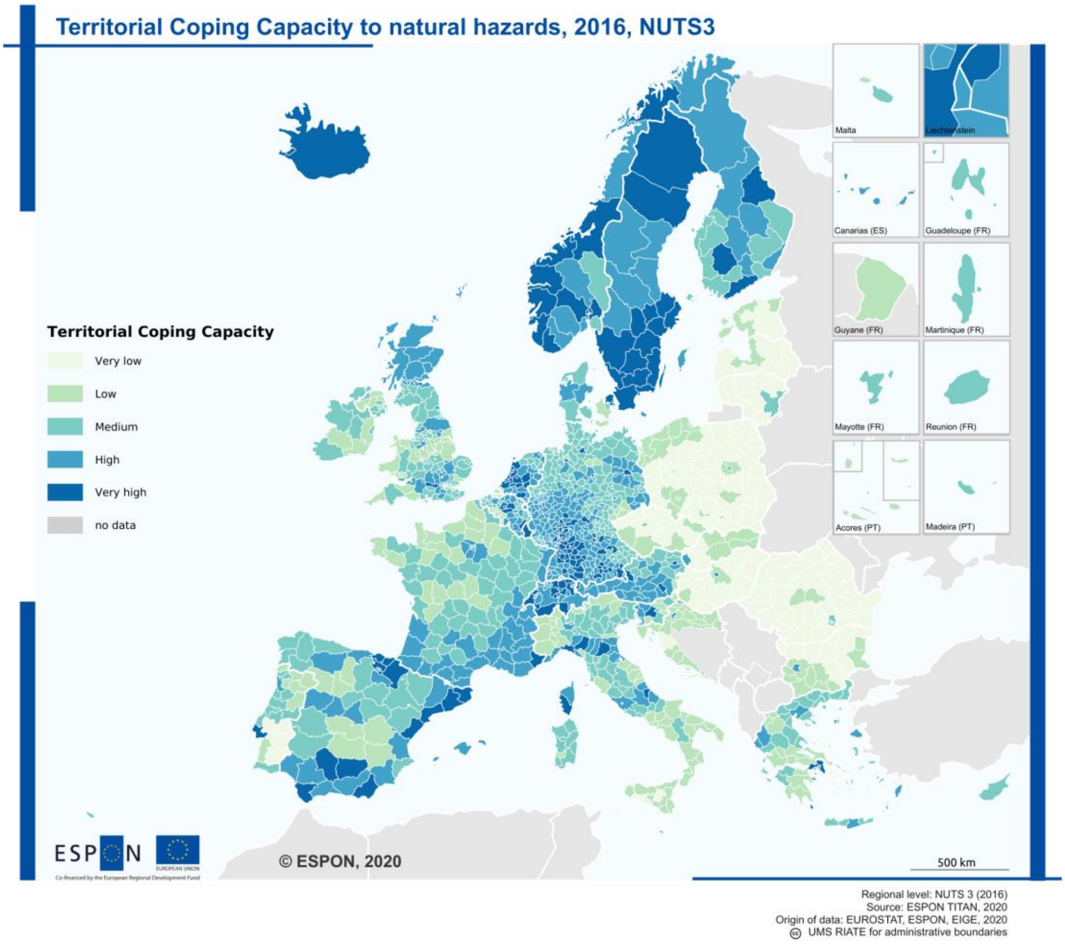
Table 3.2 Factor loadings after varimax rotation for coping capacity

Indicator	**PC1**	**PC2**	**PC3**	**PC4**
DEM_NATGROWRT	0,191	-0,148	-0,292	-0,309
DEM_CNMIGRATRT	0,178	0,058	0,201	-0,044
EDU_TERTEDC	0,25	-0,181	-0,17	-0,321
EDU_RDEXPEN	0,229	0,366	0,239	-0,006
EDU_RDPERS	0,145	0,021	0,23	-0,367
EDU_PATENTS	0,136	0,337	0,097	-0,16
SCP_SOCIALCAPITAL	0,375	-0,002	-0,01	0,029
SCP_RISKPERCEPTION	0,257	-0,259	0,417	0,141
HEA_HOSPIBEDS	-0,068	0,629	0,005	0,045
HEA_PHYSICIANS	-0,075	0,094	0,608	-0,064
ECO_GDP	0,193	0,012	0,059	-0,307
ECO_PROFSECT	0,373	-0,128	0,007	0,109
ENV_SDGI	-0,29	-0,143	0,222	-0,429
ENV_POTENGI	0,088	-0,078	0,075	0,563
GEN_EQUALITYINDEX	0,391	-0,108	-0,041	0,053
GOV_QGI	0,368	0,225	-0,049	0,004
GOV_SIGCM	-0,054	-0,343	0,346	0,052

The indicators weighting is performed using the factor loadings table after varimax rotation. The square factor loadings are calculated; then these values are divided by the proportion of variance explained by each factor; subsequently intra-factor weighted loads are divided by the proportion of variance explained by each factor in relation to the total cumulative variance; then, the weight of the indicators is computed based on the factor loadings across all factors; finally the geometric aggregation of the indicators is calculated.

The coping capacity to natural hazards at NUTS3 level is shown in Map 3.2. It is the result of applying the methodology described in previous section to the factor loadings of the coping capacity indicators.

Map 3.2 Coping capacity to natural hazards, 2016, NUTS3



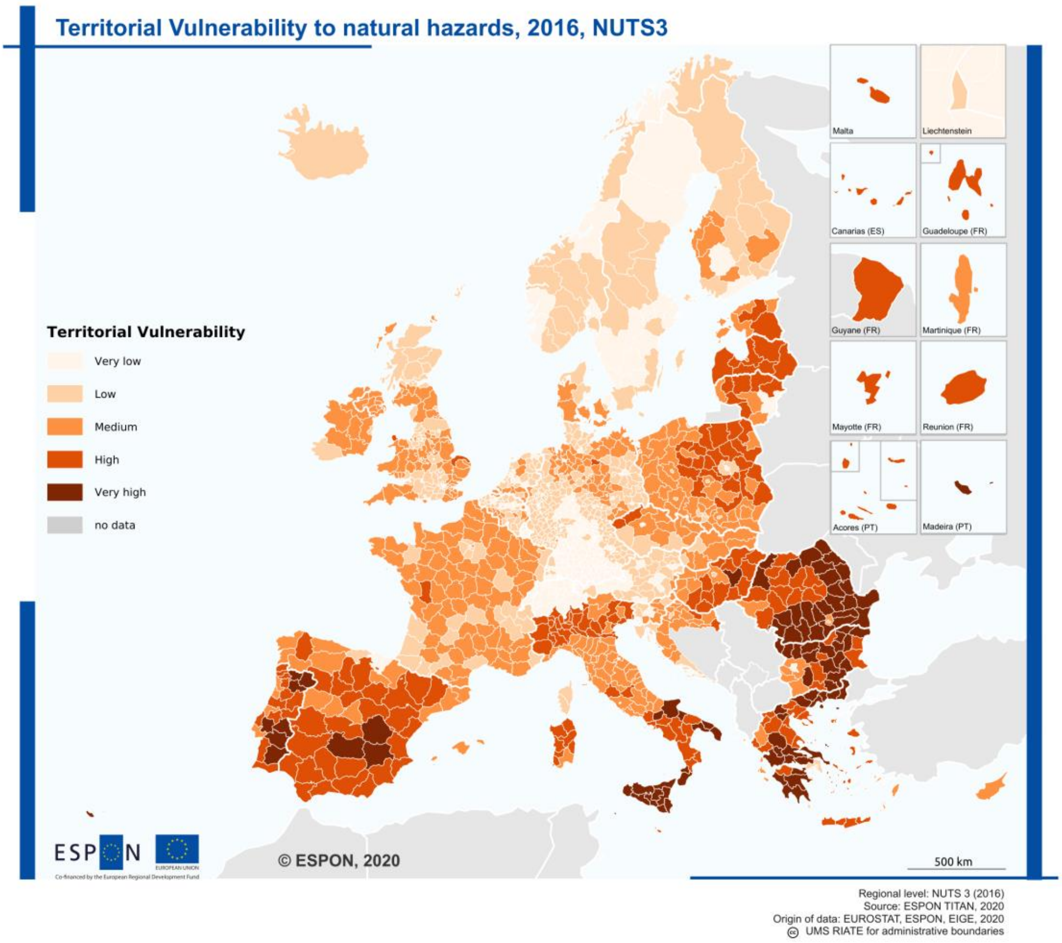
The territories identified with lower coping capacity to natural hazards are located mostly in Baltic countries and Eastern Europe countries, i.e. Estonia, Latvia, Lithuania, Bulgaria, Romania, Hungary, Czech Republic and Poland. The low coping capacity makes the territories unable to deal with a disaster before, during and after the event occurs.

3.3 Vulnerability

Vulnerability has been calculated by combining susceptibility and coping capacity, as described in the previous section, by dividing the susceptibility by the coping capacity giving a score between 1 and 2. To classify the vulnerability levels, the natural breaks algorithm was used as described in the methodology section. Map 3.3 shows the spatial territorial vulnerability pattern in relative terms for 2016 and at NUTS3 level.

A spatial distribution can be observed whereby the territories to the east and south are more vulnerable to natural hazards. Certain areas in Hungary, Romania, Bulgaria, Greece, Italy, Spain and Portugal stand out.

Map 3.3 Territorial vulnerability to natural hazards, 2016, NUTS3



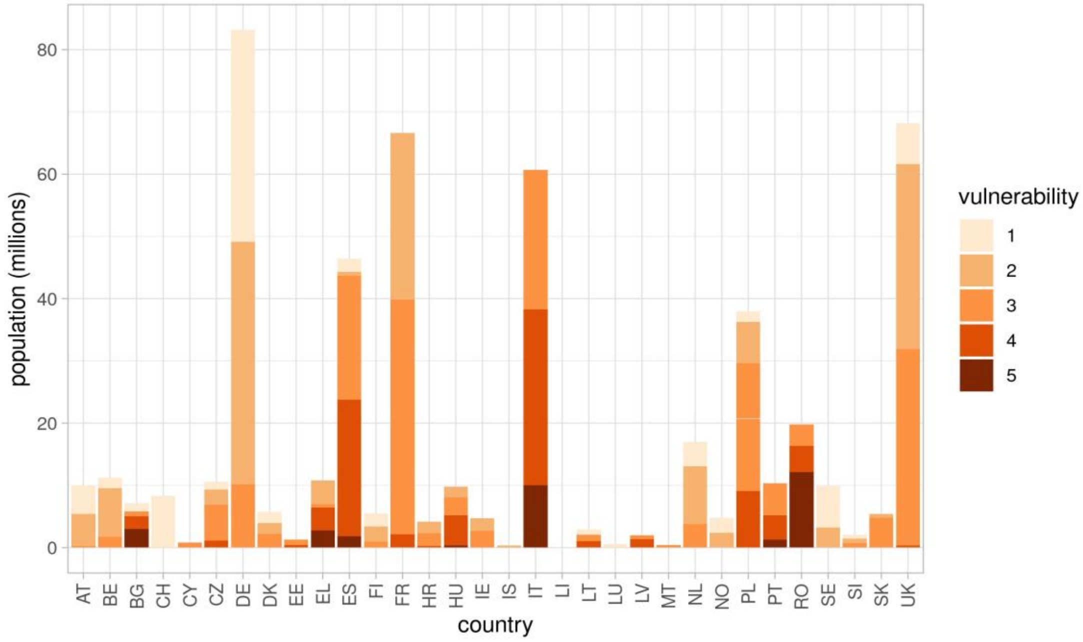
Nevertheless, some territories in Estonia, Latvia, Lithuania, Poland, France, and Czech Republic are also significantly vulnerable.

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

3.4 Population in vulnerable territories

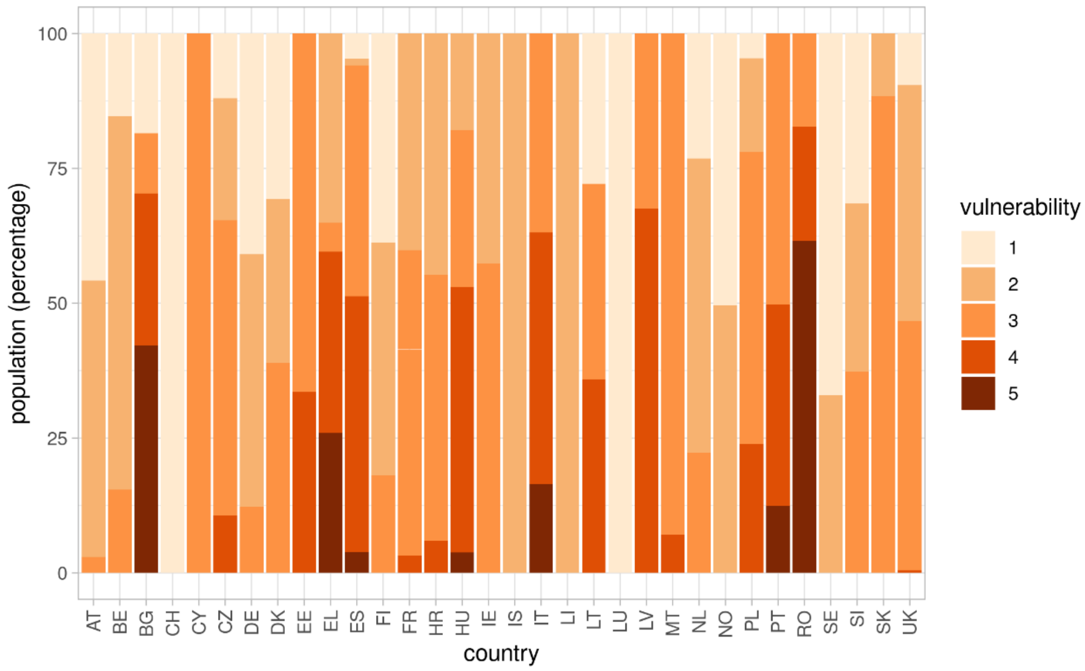
Furthermore, it contributes to understand the results the analysis of the population volume living in those territories. Figure 3.3 shows the population as of 2016 in each vulnerability group by country. In total, the population living in territories with high or very high vulnerability amounts to 116 out of 528 million in total, which translates to 22 percent. By country, Romania, Italy, Bulgaria and Greece are the ones with more population in highly vulnerable territories, followed by Spain, Portugal, Hungary, Poland and France.

Figure 3.3 Population living in vulnerable territories



Another approach to evaluate this result is by looking at the population living in vulnerable territories as percentage of the total population of the country (Figure 3.4). The countries with highest proportion of population living in very-high vulnerable territories are Romania, Bulgaria, Greece and Italy. Whilst the countries with highest proportion of population living in high or very-high vulnerable territories are Romania, Bulgaria, Latvia, Italy and Greece.

Figure 3.4 Population living in vulnerable territories in percentage of population of country



3.5 Validation of vulnerability assessment

The residuals of the multiple regression model show spatial autocorrelation as indicated by a Moran I score of 0.59. This indicates the relevance of performing a spatial regression. Besides, the Akaike Information Criterion shows a better fit of the spatial model (3.155) versus multiple regression (4.138).

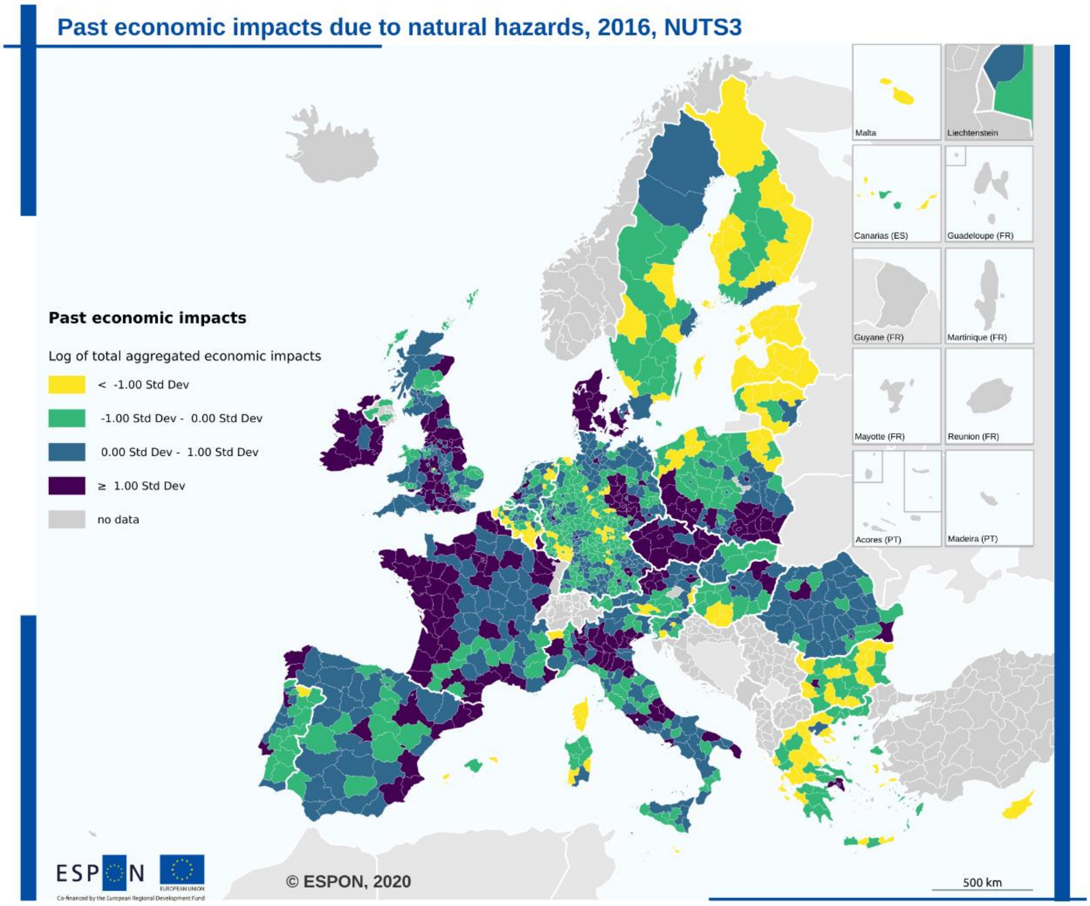
The spatial regression model is develop using the lagsarlm R package (Spatial simultaneous autoregressive lag model estimation). The input formula to the model is set as follows.

$$\log(IMP) = H + \log(GVA) + V \quad (4)$$

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

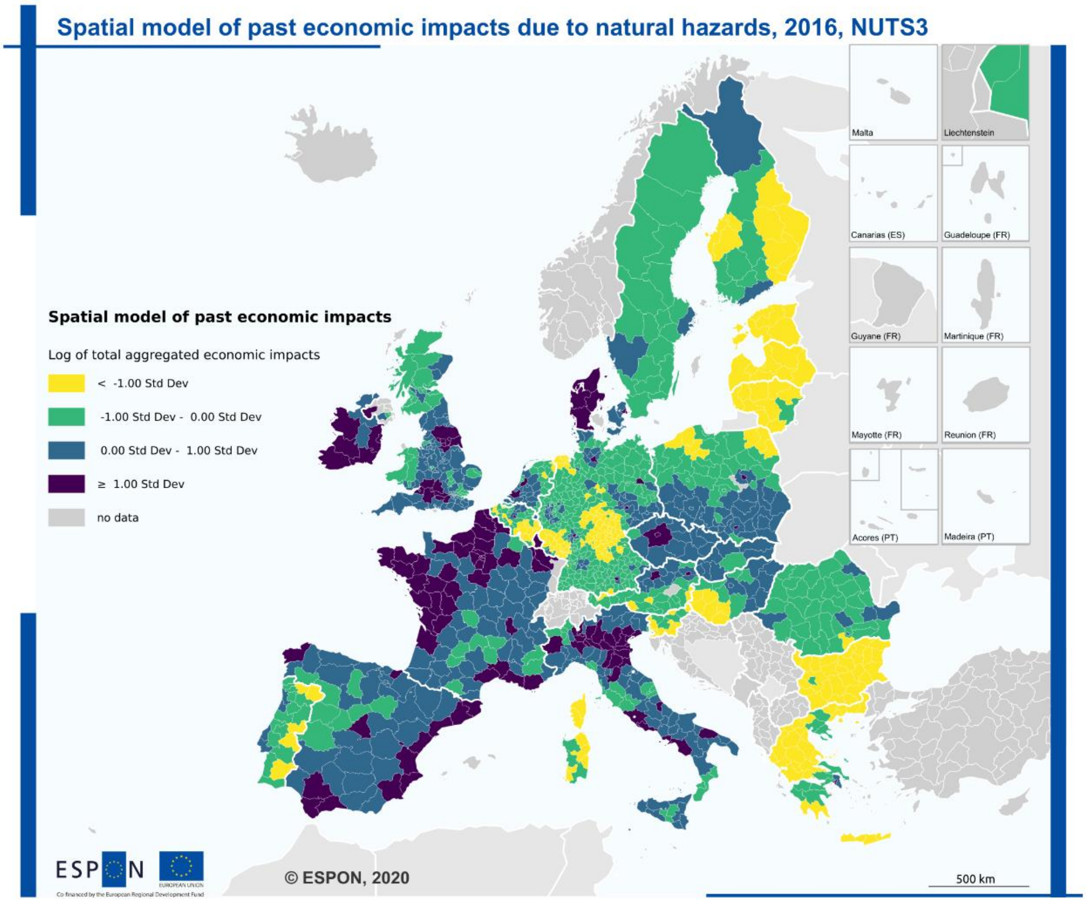
The Map 3.5 shows the predicted economic impacts obtained by the spatial regression model. The comparison between the spatial distribution of past economic impacts (Map 3.4) and the predicted economic (Map 3.5) impacts produced by the spatial regression model shows a relatively good agreement, as indicated also by a Nagelkerke pseudo-R-squared of 0.75. Therefore, it can be concluded that the hazard assessment and the territorial vulnerability analysis carried out in the project are relatively good at explaining the past economic impacts.

Map 3.4 Past economic impacts due to natural hazards, 2016



Regional level: NUTS 3 (2016)
Source: ESPON TITAN, 2020
Origin of data: EUROSTAT, ESPON, EIGE, 2020
© UMS RIATE for administrative boundaries

Map 3.5 Spatial model of past economic impacts due to natural hazards, 2016



Regional level: NUTS 3 (2016)
Source: ESPON TITAN, 2020
Origin of data: EUROSTAT, ESPON, EIGE, 2020
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4 Discussion and conclusions

4.1 Data constraints

The most important constraints have been related with the lack of information due to the scale and geographic coverage of the analysis. Data management at NUTS3 level for 32 countries have been a challenge during the collection and pre-processing of the indicators. In total, around 34500 single values have been analysed as the result of considering more than 1400 NUTS3 regions and 25 indicators.

A systematic approach for missing values management have been designed. When a missing value was found in a region, datasets with lower scale were downloaded to fill them. Some datasets were available just at NUTS2, NUTS1 or NUTS0 level. For such cases, it is recommended to keep developing these datasets at finer scales.

An additional constraint has been the completeness of indicators in different geographical areas. In general, it has been possible to obtain more data from EU countries than from EFTA countries.

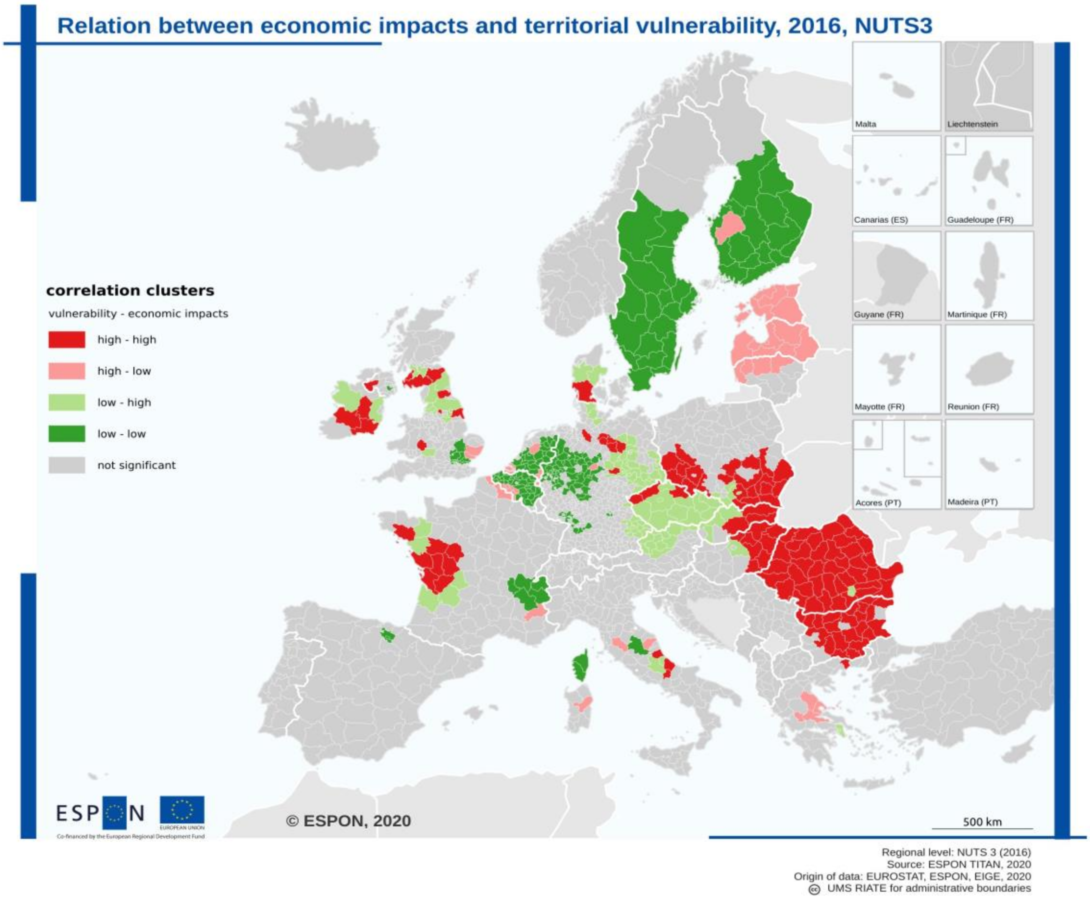
4.2 Clusters of past economic impacts and territorial vulnerability

Additionally, the results obtained in the vulnerability assessment have been compared with the spatial distribution of past economic impacts. The method used to make the comparison is based on the concept of spatial association between two variables at the local level and is referred to Bivariate Local Moran's I, which is an extension of the Local Moran statistic suggested in Anselin (1995) for two variables. According to this method, both the degree of association at local level and the level of significance of this association are obtained.

The use of the mentioned statistic makes it possible to identify the presence of clusters where both variables are distributed in the same direction, i.e. where vulnerability is low and economic impacts are low, or where vulnerability is high and economic impacts are high.

According to the distribution presented in Map 4.1, a certain correlation between economic impacts by gross value added (GVA) and territorial vulnerability can be deduced. The areas in strong red are a cluster of territories where the vulnerability and the economic impacts are high. Whereas in strong green, they are clusters of territories with low vulnerability and low economic impacts.

Map 4.1 Relation between past economic impacts and territorial vulnerability



4.3 Comparison with vulnerability distribution from ESPON CLIMATE project

It is worth mentioning the link between the vulnerability assessment performed in ESPON-TITAN project from a DRM perspective, and the one elaborated in the framework of the 2013 ESPON CLIMATE project from a CCA perspective. ESPON CLIMATE was based in the fourth IPCC framework where the exposure was considered as a component of vulnerability, whereas the fifth IPCC report (IPCC, 2014) propose a risk framework in line with DRM community where the risk is a combination of hazard, exposure and vulnerability. In this regard, the current assessment provides an updated version in terms of approach, selected indicators and more recent data. Therefore, the exposure is not a component of vulnerability any longer, so none of the indicators related with it are included. Additionally, new indicators are considered about governance, social capital, risk perception and gender that were not considered previously.

Comparing the vulnerability results in both projects, in terms of spatial distribution, they both highlight Romania, Bulgaria, Greece, Italy, Spain and Portugal as countries with highly vulnerable territories. On the other hand, the greatest differences are found in Estonia, Latvia and Lithuania, where vulnerability is relatively high in the new assessment compared to that obtained in the 2013 analysis. These differences are due to the updated approach, where the exposure is not included in the vulnerability analysis, and also due to the inclusion of new indicators.

4.4 Conclusions

Vulnerability matters. The vulnerability helps us understand why the occurrence of a natural hazard become a disaster. The most vulnerable territories to disasters, according to the methodology used in ESPON-TITAN project, are located in Eastern Europe, Southern Europe and Baltic Region.

Knowledge of territorial vulnerability patterns is crucial for proper disaster risk management. It allows the orientation of actions towards the most vulnerable regions, prioritizing those that could be most affected by the occurrence of an extreme natural phenomenon.

In this sense, territorial planning has a key role in disaster risk management due to the fact that its practice is closely linked to several of the components of vulnerability, and therefore has the potential to correct existing inequalities in this regard between territories.

In addition, as it was already mentioned in previous sections, in regard to the economic impacts, a clearer orientation on vulnerability reduction could be an efficient way to reduce the impacts of potential disasters.

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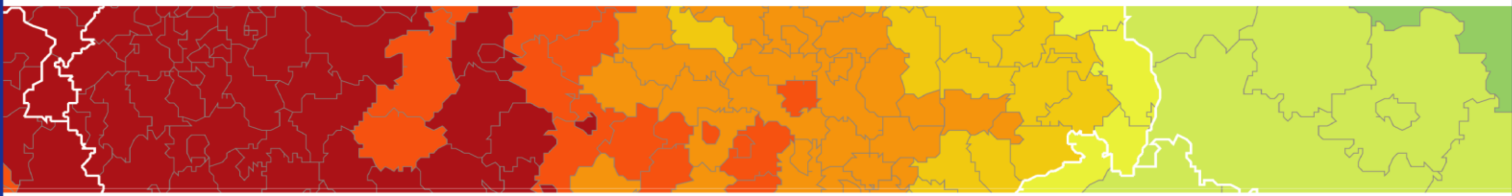

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