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Report on vulnerability of EU economic sectors and businesses at NUTS-2 level

D7.1

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LOCALISED

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List of Abbreviations

AI	Artificial Intelligence
AR6	Sixth Assessment Report of the Intergovernmental Panel on Climate Change
BERD	Business Enterprise Expenditure on Research and Development
CCS	Carbon Capture and Storage
CCU	Carbon Capture and Utilisation
CO_2	Carbon Dioxide
DRI	Decarbonisation Risk Index
EDGAR	Emissions Database for Global Atmospheric Research
ENEA	Italian National Agency for New Technologies, Energy and Sustainable Economic Development
ERDF	European Regional Development Fund
ESF	European Social Fund
ESG	Environmental, Social, and Governance
EU	European Union
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GHG	Greenhouse Gas
GVA	Gross Value Added
ICT	Information and Communication Technology
INECP	Integrated National Energy and Climate Plan
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
JRC	Joint Research Centre
LTS	Long-Term Strategy
NACE	Nomenclature of Economic Activities
NDC	Nationally Determined Contribution

NUTS	Nomenclature of Territorial Units for Statistics
OpenCoesione	Italian National Portal on Cohesion Policy
PCA	Principal Component Analysis
R&D	Research and Development
TERNA	Rete Elettrica Nazionale S.p.A.
WP	Work Package

Executive Summary

Although the discussion about sustainable transition, decarbonisation and climate change efforts have been mainly focused on national contributions and international coordination, the role of regional entities and local businesses in achieving climate change objectives should not be overlooked. The European Union's (EU) ambition of achieving carbon neutrality by 2050 presents a formidable challenge to regional governments and local businesses as many emission-intensive processes used in EU industries depend on fossil fuels and foreign-sourced raw materials. In this report, we present a framework for evaluating the vulnerability, exposure, and risk of regional businesses to decarbonisation pathways by combining their sectoral and regional dimension.

The main result is the development of a unified **Decarbonisation Risk Index (DRI) for the main business sectors in every NUTS2 region**. The immediate goal is to understand the vulnerability of regional businesses to decarbonisation across different regions and to provide an easy-to-understand and easy-to-interpret visualisation of these vulnerabilities and risks so that businesses can implement appropriate measures such as those provided in Deliverable 7.2 to mitigate some of these risks. Finally, we aim at providing a tool, in Deliverable 8.3, for policy makers and businesses to assess the risk of decarbonisation and to design strategies for mitigating it.

The theoretical framework of this study expands the concept of business vulnerability to include the risks associated with decarbonisation efforts. Traditionally, vulnerability assessments have only focused on the direct impacts of climate change on businesses, such as physical damages from extreme weather events. However, this research broadens the concept of climate change risks to include the risk from decarbonisation efforts and pathways, particularly at the regional and sectoral levels. By integrating vulnerability and exposure, the framework provides a comprehensive assessment of the risks that businesses face in transitioning to a low-carbon economy.

Our analysis reveals important patterns across the EU regions and economic sectors. First, we show that decarbonising manufacturing compared to transportation and agriculture imposes significantly higher risk to regions. Second, industrial activities such as refined petroleum and chemical products are among the most vulnerable sectors. Finally, regions in the east and south of the EU are generally the ones with relatively higher vulnerability to decarbonisation regardless of the economic sector. This underlines the long-lasting historical and structural problems in these regions and calls for greater attention from EU policy makers in designing future decarbonisation policies and the allocation of financial support for implementing them.

The unified risk index proposed here will enable regional business stakeholders to identify and reckon with their vulnerabilities, to prioritise resource allocation across their vulnerable activities, and to design effective strategies to support a just and efficient transition to a low-carbon economy.

1 Introduction

The LOCALISED project aims at supporting local authorities, businesses and citizens in understanding and undertaking mitigation and adaptation actions. The Work Package (WP) 7 - "End-user solutions for regional businesses and investors" focuses on evaluating the exposure, vulnerability and response of EU industries and businesses to climate change at the NUTS-2 level, synthesised into a composite risk index. This deliverable is the final outcome of Task T7.1 - "Evaluating vulnerability of EU industries and businesses to climate change at NUTS-2 level". The task identifies key economic sectors and activities, assesses their vulnerability and exposure considering the availability of relevant data on various operational and socio-economic dimensions at the NUTS2 level. The framework developed in this report is first implemented on Italy as the main territorial focus and manufacturing as the main sectoral focus. This case study is aimed at showing the methodological and theoretical effectiveness of this approach, then extended to all EU 27 countries and 2 other economic sectors, agriculture and transportation.

The rest of this report is divided in three main sections:

- **Theoretical Framework:** how to think about the vulnerability, exposure, and risk, their definitions and mechanisms; This part includes the conceptual definitions, the description of the framework design and its aim, as well as an introduction of the Italian manufacturing sector as a case study.

- **Empirical Framework:** how to operationalize and measure the risk, data sources and methods; This part includes the data description, the choice of dimensions, the choice of variables, the data pre-processing and the data normalisation strategy.

- **Analysis and Results:** analysis and interpretation of the results, what are the implications for policy and business; This section includes the calculation of the risk index, the validation of the results, the discussion of limitations and the alternatives, the interpretation of the results and the implications for policy and business.

2 Background and Theoretical Framework

2.1 Background

Global climate change impacts are widespread and include many aspects of daily socioeconomic operations. The response to this challenge has intensified in recent years and especially after the Paris Agreement. As a result, concentrated efforts in the form of Nationally Determined Contributions (NDC) and other national or international programs have been developed to facilitate and incentivise the decarbonisation of the economy by transitioning away from fossil fuels and towards cleaner energy resources. Green transition, therefore, requires significant changes in the society and its underlying economic procedures and structures. It includes both large-scale macro-level decisions about economic and energy policies and small-scale micro-level decisions about programs and operations that affect cities, citizens, and businesses at the local level.

In this report, we focus on the overlooked role of the territorial economic fabric and regional businesses in achieving regional and national climate objectives through their strategic and operational decisions about the procurement of energy, labour, and raw material as well as the condition of the business environment they are operating in. Special attention is given to the concept of vulnerability and risk in this context. While socioeconomic vulnerability of local communities and regions to climate change has been the subject of growing interest within the climate change impact community, less attention has been paid to business vulnerability at the firm level (Lo & Chan, 2021). Yet, the few studies that consider business vulnerability have mainly focused on the potential and realised impacts of climate change and the ways businesses cope with them (Lo & Chan, 2019). As a result, the vulnerability of businesses has been chiefly defined and understood as the sensitivity of business operations to changes in their environment from the risk of floods and sea-level rise (Davlasheridze & Geylani, 2017; Song, Huang, & Lam, 2016), to the risk that rising temperature poses to the tourism (Brouder & Lundmark, 2011).

Against this backdrop, the concept of business vulnerability and risk can be expanded to measure the readiness of businesses to embrace decarbonisation and transition to a greener economy.

In this sense, business vulnerability is not only to climate change risks but also to risks of decarbonisation efforts that are imposed upon businesses either from the government through industrial and trade policies, emissions regulations and standards, and green subsidies and incentives, or from the broader business environment including trade partners, customers, and energy suppliers.

Such risks nevertheless can be also sourced internally. Firm owners, managers, and shareholders often act upon their individual beliefs, values, and personal convictions towards social and environmental issues which in return can shape corporate ESG (Environment, Social Responsibility, and Corporate Governance) direction and commitments. Therefore, the key contribution of this report is to develop a theoretical and empirical framework for business vulnerability which considers both internal and external forces in a transparent and harmonised fashion and enables the comparison of corporate performance across regions and sectors.

2.2 Decarbonisation efforts in the EU

The EU has recognized the urgent need to address climate change and has put forward several policy packages and climate initiatives aimed at making the EU an exemplary region in terms of achieving climate-neutrality status by 2050. This objective is further enshrined in the **European Green Deal**, a package of policy initiatives for putting the EU on the path toward a green transition, with the ultimate goal of reaching climate neutrality by 2050.

The success of the Green Deal relies on the collaboration between policymakers, businesses, and other stakeholders. Industries are expected to actively participate in the transition to a more sustainable and climate-neutral economy, contributing to the overall success of the Green Deal's objectives. To enforce the EU’s intermediate and long-term objectives, and in line with the European Green Deal, the **European climate law** was adopted in 2021 and a new strategy on adaptation to climate change was developed with a vision for making the EU a climate-resilient society by 2050 (Council of the European Union, 2021). Finally, the EU adopted a wide range of policy reforms under the umbrella of the “**Fit for 55**” package to achieve at least 55% reduction in GHG emissions by 2030.

At the country level, following these policies and implementing stable, long-term strategies (LTS) are essential for achieving the necessary economic transformation and broader sustainable development goals. These strategies also support the long-term objective of the Paris Agreement, which aims to keep the global temperature rise well below 2°C above pre-industrial levels and to pursue efforts to limit the increase to 1.5°C. Therefore, in order to achieve the overall target of carbon neutrality by 2050, the EU Commission asked all the member states to develop and submit their first national LTS in 2020. The LTS report outlines how a member state plans to decarbonize its economy from 2030 to 2050, considering changes in the GDP and population dynamics, and possible realisation of climate change impacts on economic sectors such as energy and agriculture. For example, the Italian national LTS was prepared and submitted to the EU Commission in 2021. This LTS report outlines a Reference Scenario based on the extension of Italy's Integrated National Energy and Climate Plan (INECP) from 2030 to 2050, exogenous GDP and population dynamics, and the integration of climate change impacts on economic sectors such as energy and agriculture. The gap between the emission reductions under the Reference Scenario and the carbon neutrality target is then calculated and various levers and synergies for closing this gap have been identified to constitute the Decarbonisation Scenario (Peschi et al., 2021). These measures include a deeper reduction in energy demand, a faster transition to renewable energy, and the deployment of carbon capture storage or usage (CCS-CCU).

As elaborated in the Italian LTS, Decarbonisation Scenario includes important ramifications for energy and non-energy sectors of the Italian economy including the industrial production. For example, the LTS does not foresee significant cuts in industrial production assuming a strong demand for Italian industrial goods. Furthermore, due to the relatively high level of energy efficiency in Italy, most of the energy efficiency discussions are targeted towards the residential and building sector. Nevertheless, the INCEP and LTS include important provisions which will inevitably impact the Italian industrial landscape, if fully implemented (Italian Ministry of the Environment, 2021). A notable example is steel and cement manufacturing where a "technological leap" is needed to transition away from emission-intensive fossil fuels to more sustainable sources of renewable energy such as hydrogen. *Table 1* demonstrates the production projections for main industrial products under the two scenarios over a 30-year period until 2050. As shown in this table, while the production of steel and non-ferrous metals falls by 5-10%, the production in other industrial sectors increases by 10-20%.

Table 1: Key industrial production outlook in Italy (Italian Ministry of the Environment, 2021)

Production (Mt)	**2017**	**2030**	**2050**
Steel	24.1	22.1	21.5
Non-Ferrous metal	1.1	1.02	1.05
Cement	19.2	21.7	23.3
Ceramics and clay	12.6	13.3	13.7
Glass	5.4	5.6	6.0
Lime	2.5	3.1	2.7
Petrochemicals	3.1	3.2	3.3
Paper	8.9	9.1	9.2

2.3 Theoretical Framework

The transition to a low-carbon economy is an imperative global objective, driven by the need to mitigate climate change and its associated risks. The IPCC in its AR6 reporT (IPCC, 2023) emphasises the importance of assessing climate-related risks, highlighting that these risks are a function of hazard, exposure, and vulnerability. While much focus has been placed on climate risks, the risks associated with the decarbonisation pathways—often termed "transition risks"—have not been sufficiently explored, particularly at the firm level within specific sectors and regions. This report aims to develop a comprehensive framework for assessing decarbonisation risks to local businesses, with a specific focus on the EU's main economic sectors namely, manufacturing, agriculture, and transportation. While the framework is general, it has been described in detail first for the manufacturing sector as this sector is the key contributor to the GHG emissions and therefore, on the front line of any decarbonisation policy. Furthermore, more detailed data on sub-sectoral and regional manufacturing indicators are available then the other two sectors at the NUTS2 level.

In the AR6 of the IPCC, the assessment is centred on "risk" to climate change consequences, and vulnerability presents one of the contributing factors along with hazard and exposure. The IPCC risk assessment process starts with a climate-related hazard as an event or trend (natural or human induced) that may cause damages to the system. In this context, "exposure" is associated with the presence of resources and services that might be affected, "vulnerability" defines the propensity of the system to be harmed by the hazard, while the "response" captures the response of the system in reducing the contribution of aforementioned factors (hazard, vulnerability, and exposure) to the overall risk and its potential damage to the system.

This report focuses on regional businesses, as the main focus of the LOCALISED project, and how they are affected by the consequences of the objectives of the energy transition and the decarbonisation pathways. The primary aim of this report is to develop a theoretical and empirical framework for assessing business risk to decarbonisation. This framework considers both internal and external factors, enabling a comparative analysis of business risk across different regions and sectors. In this context, the risk is accounted for at the sector (NACE) and regional (NUTS-2) level.

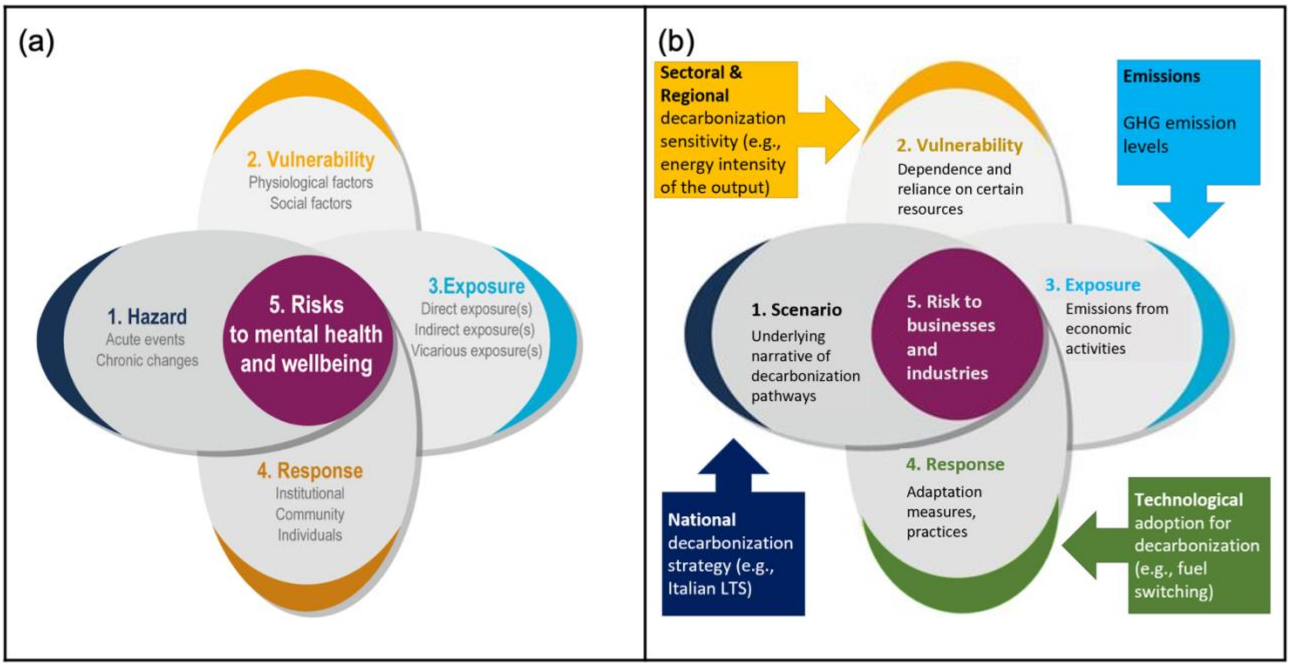

Figure 1:Risk assessment framework (a) according to IPCC AR6 (Camille et al., 2022), and (b) proposed by this report (own elaboration based on IPCC, 2023) .

Our proposed revisions are presented in Figure 1b where we have replaced the hazard component in the IPCC AR6 report (Figure 1a) with "scenario", indicating decarbonisation pathways adopted by national governments to meet the climate objectives. In the context of the EU, this includes member states' climate initiatives in line with the European Union's (EU) broader climate policy objectives including the long-term goal of achieving climate neutrality by 2050 envisioned by the "EU Green Deal" policy, and short-term goal of reducing GHG emissions by at least 55% by 2030 as proposed in “Fit for 55” policy package. In addition, every EU member state is required to develop and submit a national long-term strategy (LTS) for achieving the Paris Agreement’s temperature objectives. Since LTS documentations often lack detailed procedures and dynamics required for their realisation, for every country a set of decarbonisation pathways can be developed in a way that they match the overall objectives and priorities set out in LTS. Such pathways can be further downscaled to provide regional decarbonisation pathways which determine the trajectory of GHG emissions across different economic sectors within each region. Each of such regional decarbonisation pathways therefore, present a risk scenario to local businesses as it requires change in their underlying corporate practices and production processes.

Our general definition of risk in this context is conceptualised as a function of several key factors:

$$Risk = f(Decarbonization\ Scenario, Exposure, Vulnerability, Response)$$

In this report, we assume the scenario is modelled externally, and therefore fixed and exogenous. For this reason, at this stage, it is not included in the calculation of the risk. Moreover, the response component is only used to construct the index in the Italian case study, as we face data constraints in its operationalisation. Once a scenario is identified, for any given business sector in a particular region, the level of GHG emissions of an economic sector will constitute the exposure of that sector, and the level of carbon intensity (GHG emissions per unit of output produced) of a region will constitute the exposure of that region. The vulnerability is a unified measure composed of a set of variables influencing the propensity of the local economic system to be negatively affected by the decarbonisation pathways, or to be prepared for decarbonisation such as availability of technology and access to financial resources. The vulnerability component is therefore a measure of a business readiness to face decarbonisation challenges and its ability to absorb external shocks in terms of climate policy and regulations as well as shifts in market structure and customer preferences. For this reason, vulnerability measure is built around multiple dimensions and then aggregated into a unique indicator. More specifically:

- **Decarbonisation Scenario:** The decarbonisation scenario defines the specific pathways and strategies implemented to achieve emission reductions at the national and regional levels. The scenario identifies the gap between a reference scenario—accounting for exogenous factors like GDP and population growth—and the net-zero target. It also explores the levers and synergies required to close this gap, such as reducing energy demand, transitioning to renewable energy, and utilising carbon capture and storage (CCS) or carbon capture and utilisation (CCU) technologies.

- **Exposure:** Exposure measures the extent to which a sector or region is subject to the impacts of decarbonisation, primarily indicated by current greenhouse gas emissions levels. In this simple operationalization, higher emission levels indicate greater exposure to decarbonisation risks.

- **Vulnerability:** Vulnerability reflects the propensity of a sector or region to be adversely affected by decarbonisation. It is a multi-dimensional concept influenced by several factors:
  - **Energy:** Dependence on fossil fuels and the availability of alternative energy sources. Sectors heavily reliant on non-renewable energy are more vulnerable to decarbonisation pressures. It hence includes both transitioning away from fossil fuels and switching to renewable sources of energy.
  - **Supply Chain:** Reliance on materials from extractive industries and complex distribution networks. Supply chain dependencies can amplify risks, especially when shifts toward sustainable sourcing are required. In particular, the acquisition and the procurement of raw materials, their shipment to production facilities.
  - **Labour:** The growing skill gap between traditional and green business models, affecting the labour market's readiness for the transition. This includes challenges related to workforce retraining and adapting to new technologies. These dynamics inevitably result in societal polarisation and distributional inequalities.
  - **Technology:** Deployment of energy-saving digital technologies that increase the efficiency of production processes and the adoption, such as artificial intelligence (AI) and the Internet of Things (IoT), as well as the recalibration of research and development (R&D) activities towards innovative measures to reduce emissions. Technological readiness can significantly reduce vulnerability by enhancing operational efficiency and reducing emissions from production processes.
  - **Finance:** The financial capacity to implement necessary changes, including access to capital for decarbonisation efforts. Firms with limited financial resources may struggle to invest in cleaner technologies and processes.

Figure 2 visualises the interplay of the dimensions influencing vulnerability.

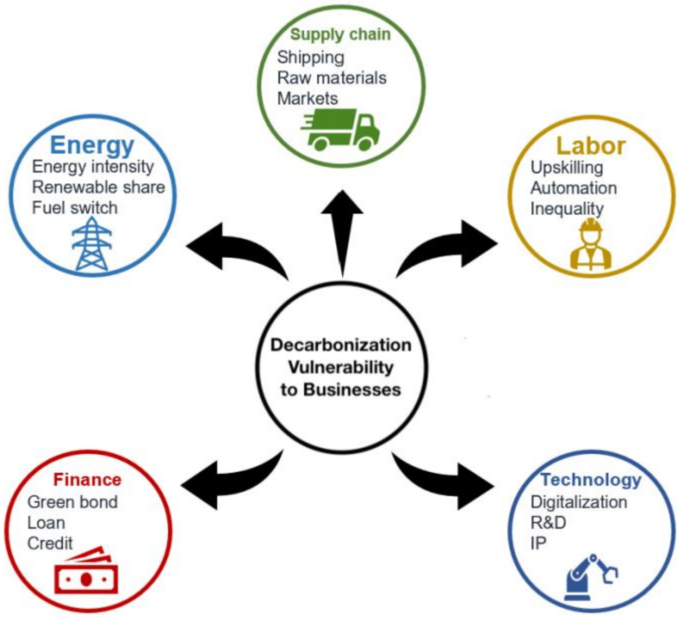

Figure 2: Dimensions of decarbonisation vulnerability of businesses (own elaboration)

- **Response:** response refers to the ability of businesses to respond to and mitigate the risks associated with decarbonisation through technological, operational, and strategic changes. Ideally, we would measure the level of technological adoption and operational efficiency in each sector and each region with metrics measuring technology penetration rates, innovation outputs, or infrastructure investment in new technology.

3 Empirical Framework

This section outlines the methodological steps taken to operationalize the components of the composite indexes used in assessing the decarbonisation risks to businesses. The empirical framework provides a systematic approach to measuring risk by quantifying exposure and vulnerability across regions and sectors.

As outlined in the previous section, the composite index will include an exposure component, a vulnerability component, and, for the specific case of Italy, a response component. Since the financial support data used for the Italian case are not available for other countries, we construct the EU risk function using only vulnerability and exposure data. In this simple first attempt, the "scenario" is exogenous and modelled outside the definition of risk.

3.1 Risk Index Construction Methodology

The composite risk index integrates exposure, vulnerability, and response components to provide a comprehensive measure of decarbonisation risk for each sector and region. This approach recognizes the interdependence of sectors and regions in the decarbonisation landscape, allowing for tailored risk assessments that can guide policy and decision-making. The risk index is framed as:

$$R_{s,r} = f(R_s, R_r)$$

Where:

- $R_{s,r}$ represents the total risk index combining sectoral and regional risks,
- R_s is the sectoral risk index,
- R_r is the regional risk index.

The constituent parts of the risk indicator (exposure, vulnerability and response) have to be combined in order to produce a single composite risk indicator. Since our composite index refers to manufacturing sectors in regions, we built two risk indexes, one for sectors and one for regions, and combined them together in a total risk index.

Risk of sectors and risk of regions are expressed as follows:

$$R_s = f(E_s, V_s)$$

$$R_r = f(E_r, V_r)$$

Regional risk for maps of Italy:

$$R_{\mathrm{r,\,Italy}} = f(E_{\mathrm{r}}, V_{\mathrm{r}}, \mathrm{Response})$$

Where:

- E_S represents the exposure of the sector of reference,
- E_r represents the exposure of the region of reference,
- V_s represents the vulnerability of the sector of reference,
- V_r represents the exposure of the region of reference.

Therefore, the total risk is a function of exposure and vulnerability of sectors, and of exposure and vulnerability of regions. In the composition of the index, the choice of the appropriate aggregation function can deeply influence the results.

In our index, we initially model the sectoral and regional risks independently, to then merge the measures into a single indicator for each sector-region couple, namely for each sector in each region, represented by the "total risk" measure. Regional characteristics such as the availability of renewable energy, infrastructure quality, and local regulations directly impact the operational environment of sectors within that region. For instance, a region with strong renewable energy infrastructure and favourable decarbonisation policies can reduce the overall risk for sectors operating within it, while regions with poor infrastructure and high dependence on fossil fuels can elevate sectoral risks. Conversely, the presence of high-emission sectors in a region can drive up the region's overall exposure to decarbonisation risks. For example, if a region has a concentration of heavy industries like steel or cement manufacturing, the regional risk level will naturally be higher due to the cumulative impact of these sectors' emissions and energy use. Therefore, there is a degree of endogeneity that needs to be accounted for when the total risk is calculated.

Regarding the construction of R_s and R_r themselves, we can assume that exposure and vulnerability, in this context, are not directly dependent on each other, and we can assume that they are equally relevant to risk. However, according to the IPCC definition of risk, the relevancy of vulnerability to the total risk exists especially in function of exposure. This means that without exposure, there is no vulnerability. In our context, if a sector is near to decarbonisation (namely it has low emission levels), its vulnerability to decarbonisation will be automatically lower. In the context of decarbonisation, exposure refers to the extent to which a sector or region is subject to the impacts of transitioning to a low-carbon economy. This is often indicated by factors like greenhouse gas (GHG) emissions, dependence on fossil fuels, or the intensity of energy consumption. Vulnerability, on the other hand, refers to the susceptibility of that sector or region to suffer from the consequences of decarbonisation, such as economic losses, operational disruptions, or increased costs. If there is no exposure (e.g., if a sector already operates with low emissions and low fossil fuel dependence), then the impact of decarbonisation measures on that sector will be minimal. Essentially, if a sector does not emit significant GHGs or relies minimally on carbon-intensive processes, it will not face substantial challenges or disruptions when transitioning to a greener economy. Therefore, its risk is inherently low because it is not significantly at risk from the changes required by decarbonisation policies. Sectors with low exposure are less likely to be targeted by stringent decarbonisation measures, and from an economic standpoint, these sectors will not need to redirect resources significantly to mitigate risks. This reinforces the notion that vulnerability is conditional upon the presence of exposure.

From a policy perspective, the risk index should account for the territorial importance of the sectors, as regions with high economic reliance on carbon-intensive economic activities may face more severe socio-economic challenges during the decarbonisation transition. Policymakers must therefore consider not only the absolute risk level of each sector-region pair but also the broader economic and social implications. For instance, regions with a high concentration of employment in vulnerable sectors might require tailored support measures, such as job retraining programs, investments in green infrastructure, or subsidies for cleaner technologies, to mitigate the negative impacts of decarbonisation. On this backdrop, to combine sectoral and regional risks we use the gross value added of sectors in regions, as a proxy of relative importance of a sector in a region. This proxy is used as a weight in the aggregation of the two indicators into the final risk index.

Ideally, the index should be sensitive to dynamic factors such as technological advancements, changes in market conditions, and evolving regulatory frameworks. Technological innovation, for example, can significantly alter both exposure and vulnerability over time by reducing emissions or enhancing energy efficiency. Similarly, regulatory shifts, like the introduction of carbon pricing or stricter emission standards, can redefine the risk landscape, increasing exposure for sectors previously considered low-risk.

3.2 Choice of Aggregation Method

In constructing the risk index, the method of aggregating the exposure and vulnerability components is crucial, as it determines how these factors combine to reflect the overall risk. While exposure and vulnerability both influence the overall risk, they do not necessarily affect each other directly. A sector might have high emissions (high exposure) but low vulnerability if it is technologically advanced, financially resilient, or well-positioned to adapt. Conversely, a sector could have low emissions (low exposure) but still be vulnerable if it lacks response capability or faces significant economic barriers. However, in the context of decarbonisation risk, it is essential to recognize that if exposure is low—meaning the sector or region has low greenhouse gas emissions—the overall risk should also be low, regardless of the vulnerability level. This is because sectors or regions with low emissions are less likely to be significantly impacted by decarbonisation policies aimed at reducing emissions. Even if such sectors are vulnerable in terms of financial or technological capacity, the pressure and urgency of adapting to decarbonisation efforts are inherently less due to their minimal contribution to emissions.

Using a multiplicative aggregation method, such as the geometric mean, aligns well with the need for the risk index to be low when exposure is low. In a multiplicative model, if the exposure component is low (approaching zero), the product of exposure and vulnerability will also be low, regardless of the vulnerability score. This method captures the principle that low exposure effectively limits the overall risk. In contrast, additive aggregation methods, such as calculating a simple average of exposure and vulnerability, may not adequately reflect the need for the risk to be low when exposure is low.

The mathematical representation of the aggregation of these components is as follows:

$$R_s = \sqrt{E_{\text{norm},s} \times V_{\text{norm},s}}$$

$$R_r = \sqrt{E_{\text{norm},r} \times V_{\text{norm},r}}$$

$$R_{s,r} = w_{s,r} \times \sqrt{R_s \times R_r}$$

In the maps of Italy, regional risk has response integration:

$$R_{r,\text{Italy}} = \sqrt{\frac{E_{\text{norm},r} \times V_{\text{norm},r}}{\log(1 + \text{Response})}}$$

As previously mentioned, the Regional Risk comprises Response only for the Italian case study. The European maps are instead generated without considering Response.

The multiplicative aggregation method respects the need for the risk index to be low when exposure is low. It ensures that:

- **Low Exposure Dominates the Risk Calculation:** If a sector or region has low emissions, the overall risk remains low, even if vulnerability is high. This reflects the reality that decarbonisation efforts will have a limited direct impact on entities that are not significant emitters.

- **High Exposure Amplifies Risk with Vulnerability:** For sectors or regions with high emissions, the level of vulnerability becomes critically important. High exposure combined with high vulnerability results in a significantly higher risk, highlighting areas where decarbonisation policies may have the most substantial impact and where adaptive measures are most needed.

- **Reflects the Conditional Nature of Vulnerability:** Vulnerability contributes to the risk primarily in the presence of exposure. Without significant exposure, vulnerability factors do not translate into high risk in the context of decarbonisation pressures.

3.3 Data Preprocessing and Normalisation

To make the indicators comparable across different scales and units, Min-Max normalisation is used during the final stages of data processing and visualisation of the risk indices. This normalisation method transforms the data into a common scale, typically ranging from 0 to 1, by adjusting each value relative to the minimum and maximum values within the dataset. Min-Max normalisation is employed in the final step when aggregating exposure, vulnerability, and response components into the composite risk index. After computing the risk scores, Min-Max normalisation is applied to scale the combined scores into a consistent range. This allows for easier comparison across sectors and regions, ensuring that the results are presented in a standardised format.

The equation used is the following:

$$x_{\text{normalized}} = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) \times (1 - 2\epsilon) + \epsilon$$

Where:

- x_{min} is the minimum value of x
- x_{max} is the minimum value of x
- ϵ is a small adjustment factor (0.01 in this case)

Consequently, after normalisation, the values are clipped to lie within the defined range, in this case between 0.01 and 0.99. This ensures that, when performing the index aggregation, the results are not overly influenced by extreme values (0 and 1) that could distort the overall assessment, if multiplicative aggregation methods like geometric mean are adopted. Normalised data are then assigned to a specific component of the risk index.

3.4 Measurement of the Components of the Risk for Sectors and Regions

The risk index is constructed by measuring and combining three main components: exposure, vulnerability, and response. These components are calculated separately for sectors and regions to capture both the sector-specific and regional-specific factors influencing the risk associated with decarbonisation efforts.

3.4.1 Exposure Component

The exposure component measures the extent to which sectors and regions are subject to the impacts of decarbonisation, primarily indicated by their current levels of greenhouse gas (GHG) emissions. Higher emission levels imply greater exposure to the risks associated with the transition to a low-carbon economy.

For sectors, exposure is quantified using the average GHG emissions attributable to each sector. The data on sectoral emissions is obtained from the European Commission's Joint Research Centre (JRC) Emissions Database for Global Atmospheric Research (EDGAR). The emissions are measured in kilotons of CO_2 equivalent. For regions, exposure is measured using the CO_2 intensity of each region, defined as the amount of CO_2 emissions per unit of regional Gross Domestic Product (GDP). This reflects the carbon efficiency of the regional economy.

3.4.2 Vulnerability Component

The vulnerability component assesses the susceptibility of sectors and regions to adverse effects from decarbonisation efforts. It encompasses multiple dimensions that influence the propensity to be affected, including energy dependence, trade exposure, employment dynamics, research and development capacity, and investment levels.

Indicators where higher values represent lower vulnerability (i.e., they are beneficial factors) are inverted by subtracting the normalised value from 1. This ensures that higher values consistently indicate higher vulnerability across all indicators. The inversion of certain indicators is necessary to ensure consistency in the interpretation of the vulnerability scores. For instance, higher R&D expenditure or greater employment levels are positive attributes that reduce vulnerability. We align the direction of all indicators so that higher values uniformly represent higher vulnerability. This alignment simplifies the aggregation process and interpretation of the results.

The following tables show how the indicators are associated with different components of the indexes.

Table 2: Indicators used for Regional Indexes (own elaboration)

Indicator	Source and Code	Year	Description	Direction	Dimension
Emission Intensity of Regions	EDGARv7.0 FT2021	2022	Average emissions of the reference region divided by GDP of that region in 2022.	Positive relationship	Exposure
Energy Intensity of Regions	Eurostat	2022	Total non-residential energy consumption of the reference region divided by GDP of that region in 2022.	Positive relationship	Vulnerability, Energy dimension
Unemployment Rate	Eurostat	2022	Unemployed persons as a percentage of the economically active population in the reference region.	Positive relationship	Vulnerability, Labour dimension
Rail Network	Eurostat	2022	Rail network of the reference region in Km.	Negative relationship	Vulnerability, Supply Chain dimension
Gross Fixed Capital Formation (GFCF)	Eurostat	2021	Aggregate GFCF in million euros for all economic activities in the reference region.	Negative relationship	Vulnerability, Finance dimension
R&D Personnel	Eurostat	2021	R&D personnel as a share of total employment in the reference region.	Negative relationship	Vulnerability, Technology dimension
Gross Domestic Expenditure on R&D (GERD)	Eurostat	2022	Gross Domestic Expenditure on R&D (GERD) activities as the total intramural expenditure on research and development performed in the reference region.	Negative relationship	Vulnerability, Technology dimension

Table 3: Indicators used for Sectoral Indexes for Manufacturing and Transportation (own elaboration)

Indicator	Source and Code	Year	Description	Direction	Dimension
Greenhouse Gasses (GHGs) Emissions	Eurostat	2022	EU average GHG Emissions in thousands of tonnes of CO2 equivalent per year, per enterprise in the reference sector	Positive relationship	Exposure
Final Energy Consumption	Eurostat	2022	EU average industrial final energy consumption in terajoules, per enterprise in the reference sector	Positive relationship	Vulnerability, Energy dimension
Share of Fossil Energy Consumption	Eurostat	2022	EU average share of fossil energy consumption, per enterprise in the reference sector	Negative relationship	Vulnerability, Energy dimension
Share of Renewable Energy Consumption	Eurostat	2022	EU average share of renewable energy consumption, per enterprise in the reference sector	Positive relationship	Vulnerability, Energy dimension
Total Employment in a Sector	Eurostat	2022	EU average total employment, per enterprise in the reference sector	Negative relationship	Vulnerability, Labour dimension
Average Persons Employed per Enterprise in a Sector	Eurostat	2022	EU average persons employed, per enterprise in the reference sector	Negative relationship	Vulnerability, Labour dimension
Import and Export in Euros in a Sector	Eurostat	2022	EU average total import and export in thousands of euros, per enterprise in the reference sector	Positive relationship	Vulnerability, Supply Chain dimension
Import and Export as Share of Enterprises Participating in Trade in a Sector	Eurostat	2022	EU average share of enterprises participating in trade, per enterprise in the reference sector	Positive relationship	Vulnerability, Supply Chain dimension
Gross Investments in Intangible Non-Current Assets	Eurostat	2021	EU average gross investments in intangible non-current assets, in millions of euros, per enterprise in the reference sector	Negative relationship	Vulnerability, Finance dimension
Sales Proceeds of Tangible Investments	Eurostat	2022	EU average sales proceeds of tangible investments, in millions of euros, per enterprise in the reference sector	Negative relationship	Vulnerability, Finance dimension
Business Enterprise Expenditure on R&D (BERD)	Eurostat	2022	EU average business expenditure on R&D in millions of euros, per enterprise in the reference sector	Negative relationship	Vulnerability, Technology dimension
Share of Enterprises providing ICT Training	Eurostat	2022	EU average share of enterprises providing ICT training, per enterprise in the reference sector	Negative relationship	Vulnerability, Technology dimension

For sectors, relevant indicators corresponding to these dimensions are collected from authoritative sources such as Eurostat. Each indicator is normalised using Min-Max normalisation to ensure comparability. In cases where higher values of an indicator represent lower vulnerability (for example, higher R&D investment suggesting greater resilience), the normalised values are inverted, so that higher values consistently indicate higher vulnerability. Within each dimension, the normalised indicators are averaged to create a composite score. For example, the energy dimension for sector s is calculated by averaging the normalised indicators related to energy consumption and dependence.

Table 4: Indicators used for Sectoral Indexes for Agriculture (own elaboration)

Indicator	Source and Code	Year	Description	Direction	Dimension
Greenhouse Gasses (GHGs) Emissions	Eurostat	2022	EU average GHG Emissions in thousands of tonnes of CO2 equivalent per year, per farm	Positive relationship	Exposure
Final Energy Consumption	Eurostat	2022	EU average agricultural final energy consumption in terajoules, per farm	Positive relationship	Vulnerability, Energy dimension
Share of Fossil Energy Consumption	Eurostat	2022	EU average share of fossil energy consumption, per farm	Negative relationship	Vulnerability, Energy dimension
Share of Renewable Energy Consumption	Eurostat	2022	EU average share of renewable energy consumption, per farm	Positive relationship	Vulnerability, Energy dimension
Agricultural Labour Productivity	Eurostat	2022	EU average agricultural labour productivity, per farm, in Annual Working Unit (AWU is the number of full-time equivalent workers)	Negative relationship	Vulnerability, Labour dimension
Import and Export in Euros in a Sector	Eurostat	2022	EU average total import and export in thousands of euros, per farm	Positive relationship	Vulnerability, Supply Chain dimension
Import and Export as Share of Enterprises Participating in Trade in a Sector	Eurostat	2022	EU average share of farms participating in trade, per farm	Positive relationship	Vulnerability, Supply Chain dimension
Government Support to Agricultural Research and Development	Eurostat	2022	Government budget allocations for research and development (GBARD) for agriculture, per farm	Negative relationship	Vulnerability, Finance dimension
Business Enterprise Expenditure on R&D (BERD)	Eurostat	2022	EU average business expenditure on R&D, per farm, in millions of euros	Negative relationship	Vulnerability, Technology dimension

The overall vulnerability score for each sector is then obtained by aggregating the dimension scores using an equal weighting scheme:

$$V_s = \frac{1}{d}\sum_{k=1}^{d} V_{s,k}$$

where

- V_S is the overall vulnerability score for sector s,
- $V_{s,k}$ is the score for dimension k and
- k is the total number of dimensions (five in this case).

A similar approach is used to calculate the vulnerability for regions. Relevant regional indicators are collected and normalised. Direction adjustments are made where necessary to ensure that higher values represent higher vulnerability. Dimension scores are calculated by averaging the normalised indicators within each dimension, and the overall vulnerability score for each region is obtained by equally weighting the dimension scores. While equal weighting provides simplicity and transparency, alternative methods such as Principal Component Analysis (PCA) can be employed to derive data-driven weights based on the variance explained by each dimension. However, in this study, equal weights are chosen to maintain simplicity. Figures 4 and 5 present the vulnerability and exposure indexes for the Italian manufacturing sector, respectively.

3.4.3 Response Component Integration

The response component for generating the Italian maps measures the ability of regions to respond to and mitigate the risks associated with decarbonisation. It reflects factors such as technological adoption, financial resources, and policy support that enhance a region's capacity to adapt.

The total funding in each region is divided by the regional population to obtain funding per capita:

$$\text{Response} = \frac{\text{Total Funding}_{\text{region}}}{\text{Population}_{\text{region}}}$$

where $Total\ Funding$ is the total funding for region r from the European Union to finance climate change adaptation and mitigation projects. This is a lax measure, and has been log-transformed to reduce its influence on the regional risk index by mitigating the impact of extreme values. The logarithmic transformation diminishes the effect of regions with exceptionally high funding per capita, ensuring that these outliers do not disproportionately skew the overall risk assessment. By doing so, it promotes a more balanced and equitable comparison across all regions. This because this measure of response may not fully capture the complexities of each region's actual response capacity due to unaccounted factors.

3.4.4 Relative Importance of Sectors in Regions as a Weight

To capture the interplay between sectoral and regional risks, the relative importance of each sector within a region is used as a weighting factor when combining the sectoral and regional risk indices. This ensures that sectors contributing more significantly to a region's economy have a proportionally larger impact on the total risk. The share of employment in each sector within each region is used to indicate the relative importance of each sector in each region. The employment share of each sector is divided by the total employment of all sectors in that region to obtain the relative importance (weight) of the sector:

$$w_{s,r} = \frac{\text{Employment Share}_{s,r}}{\text{Total Employment}_r}$$

Where:

- $w_{s,r}$ is the weight of sector s in region r,
- $Employment\ Share_{s,r}$ is the share of total employment of sector s in region r, and
- $Total\ Employment\ _r$ is the total employment of region r.

By weighting the combined risk index with the relative importance of the sector in the region, the assessment accounts for the economic significance of each sector within the regional context. This approach ensures that sectors more vital to a region's economy are appropriately represented in the risk assessment.

The final maps show the composite business risk in a region, combining the overall regional risk with the sector-specific risks weighted by the importance of each sector in that region's economy. The weighted term represents the average risk across all sectors in a region, where the weight is the employment share of a sector in the region. The square root of the product of regional risk and weighted sectoral risks provides a balanced measure of the overall business risk in the region, taking into account both broad regional factors and the economic structure of the region. This approach highlights how sectoral composition influences the vulnerability of businesses in a specific region. The formula is:

$$R_{\text{business in region } r} = \sqrt{R_r \times \left(\sum_s w_{s,r} \cdot R_s \right)}$$

Where:

- $R_{business\ in\ region\ r}$ is the composite business risk in region r,
- R_r is the risk for region r,
- $w_{s,r} \cdot R_s$ is the weighted average risk across all sectors in region r, where the contribution of each sector to the overall risk is proportional to its employment share in the region.

3.5 Data Sources

The report focuses on the manufacturing, agriculture and transportation sectors. The manufacturing sector is the most detailed sector represented in the Eurostat database. For the manufacturing sector, we analyse subsectors in detail. We adopt a similar framework for the other two sectors of agriculture and transportation, but we do not analyse subsectors in these cases. The data used for constructing the risk index is sourced from multiple databases, primarily Eurostat, and supplemented with specific datasets such as the European Commission's Joint Research Centre (JRC) Emissions Database for Global Atmospheric Research (EDGAR) for greenhouse gas emissions. All data are from 2020, 2021 or 2022, ensuring the analysis reflects the most recent available information.

3.5.1 Exposure and Vulnerability Data Sourced

The data is categorised into sectoral and regional indicators, with each indicator aligned to either exposure, vulnerability, or response components within the risk framework. These indicators cover various aspects such as greenhouse gas emissions, energy consumption, employment, trade, and investment in research and development. For instance, sectoral data include indicators like emissions, fossil fuel dependence, and trade volumes, while regional data focus on factors such as renewable energy production, unemployment rates, and infrastructure quality. This categorization allows for a detailed assessment of both sector-specific and region-specific risks related to decarbonisation. A critical aspect of the analysis is understanding the directionality of each indicator in relation to vulnerability and exposure. Indicators are assigned a positive or negative direction based on whether higher values contribute to higher vulnerability/exposure or lower vulnerability/exposure. Positive direction implies that higher values indicate higher vulnerability or exposure, while negative direction implies that higher values indicate lower vulnerability or exposure. Normalised indicators are inverted to ensure consistency in the assessment. The negative direction indicators are sometimes referred to as indicators of "adaptive capacity", meaning that they contribute to increasing the resilience of a sector or of a region.

Sectoral data are based on the main manufacturing sectors categorised by Eurostat according to the NACE Rev. 2 classification. The NACE classification provides a standardised framework for categorising economic activities within the European Union, ensuring consistency in data collection and analysis. The relevant NACE categories used are shown in *Table 4.* Regional data are analysed at the NUTS 2 level. The NUTS (Nomenclature of Territorial Units for Statistics) classification provides a hierarchical system for dividing up the economic territory of the EU for statistical purposes.

Table 5: Manufacturing subsector categories (NACE C10-C33) used in the analysis (own elaboration)

Category	**Products Included**	**EU NACE Code**
Food, Beverages and Tobacco	Processing of food items (bread, dairy, meat), beverages (soft drinks, alcohol, bottled water), and tobacco products (cigarettes).	C10-C12
Textile, Wearing and Leather Products	Production of textiles (fabrics, yarns, carpets), wearing apparel (clothing, accessories), and leather products (shoes, bags, leather goods).	C13-C15
Wood, Paper and Printing	Manufacturing of wood products (furniture, lumber), paper and paperboard (office paper, packaging), and printing activities (books, newspapers, publications).	C16-C18
Refined Petroleum	Refining crude oil into petroleum products (gasoline, diesel, jet fuel) and by-products (lubricants, asphalt).	C19
Chemical Products	Production of chemicals (acids, alkalis, gases), fertilizers, plastics, pesticides, paints, and other chemical products.	C20
Pharmaceutical Products	Manufacturing of pharmaceuticals, medicinal chemical products, and botanical products (prescription drugs, vaccines, over-the-counter medications).	C21
Plastic Products	Production of plastic goods (packaging materials, household items, vehicle parts, construction-related products).	C22
Non-metallic Mineral Products	Manufacturing of products made from non-metallic minerals (glass, cement, ceramics, concrete, stone products).	C23
Basic Metals	Production of basic metal products (iron, steel, aluminum, other primary metals) involving smelting, refining, and rolling.	C24
Fabricated Metals	Manufacturing of metal structures and products excluding machinery (doors, windows, cutlery, tools, fabricated metal goods).	C25
Electronic Products	Production of electronic components, computers, consumer electronics, electrical equipment, appliances, medical devices, measurement instruments.	C26-C27
Transport Equipment	Manufacturing of vehicles (cars, trucks), parts, aircraft, ships, trains, and other transportation equipment.	C29-C30
Other	Various manufacturing activities (furniture, jewelry, sports goods, toys, repair, and installation of industrial machinery and equipment) not classified elsewhere.	C31-C33

3.5.2 Response Data Sources

To quantify the “Response” for regions in Italy, we utilise data on the total funding received for climate change adaptation and mitigation projects. This data is sourced from OpenCoesione, specifically from their "Focus Cambiamento Climatico" (Focus on Climate Change) dataset. OpenCoesione is the Italian national portal on the cohesion policy, providing open data on the implementation of projects funded by European Structural and Investment Funds and national co-financing. The platform offers detailed information on projects, funding amounts, beneficiaries, and territorial distribution, promoting transparency and enabling analysis of public investments. The "Focus Cambiamento Climatico" dataset within OpenCoesione specifically aggregates data related to projects aimed at combating climate change. This includes projects financed under various programs and funds, such as the European Regional Development Fund (ERDF) and the European Social Fund (ESF), targeting both mitigation and adaptation initiatives.

We extracted data on the total financial allocations for climate-related projects for each Italian region (NUTS 2 level) from the OpenCoesione portal. The dataset includes variables such as the region's name, total public funding allocated, and the classification of projects under climate change objectives. For regions with multiple entries due to sub-regional projects or projects spanning multiple regions, the total funding amounts were aggregated to obtain a single value for each region. Data entries corresponding to national-level projects or those not localised to a specific region were excluded to focus the analysis on regional capacities.

The total climate-related funding for each region was divided by the regional population to obtain the funding per capita. This metric reflects the financial resources available per person in the region dedicated to climate change initiatives, serving as a proxy for response. Funding dedicated to climate change projects is a tangible measure of a region's commitment and capacity to implement adaptation and mitigation strategies. It encompasses investments in renewable energy infrastructure, energy efficiency improvements, technological innovation, and community resilience programs. By considering funding on a per capita basis, we account for the relative scale of investments concerning the regional population size. This allows for a fair comparison between regions with different population densities and economic scales. At the same time, the effectiveness of funding in enhancing response depends on how funds are utilised. While total funding per capita is a useful proxy, it does not capture the efficiency or impact of specific projects. Moreover, response is multifaceted, and while funding is a critical component, other factors such as institutional strength, public awareness, and private sector engagement also play significant roles.

4 Decarbonisation Risk to Italian Manufacturing

By examining the components of the risk scores, the analysis reveals critical insights into how decarbonisation may impact Italy’s industrial landscape and identifies where targeted interventions are most needed. The results, shown in Figure 3, indicate that certain sectors and regions are particularly vulnerable to the effects of decarbonisation due to their high emission intensities and energy dependencies. Sectors such as Refined Petroleum, Basic Metals, and Fabricated Metals exhibit the highest exposure and vulnerability, largely because of their reliance on fossil fuels and energy-intensive processes. This is especially evident in regions like Sardegna, Sicilia, and Lombardia, which show pronounced risks due to their strong economic dependence on these high-emission industries.

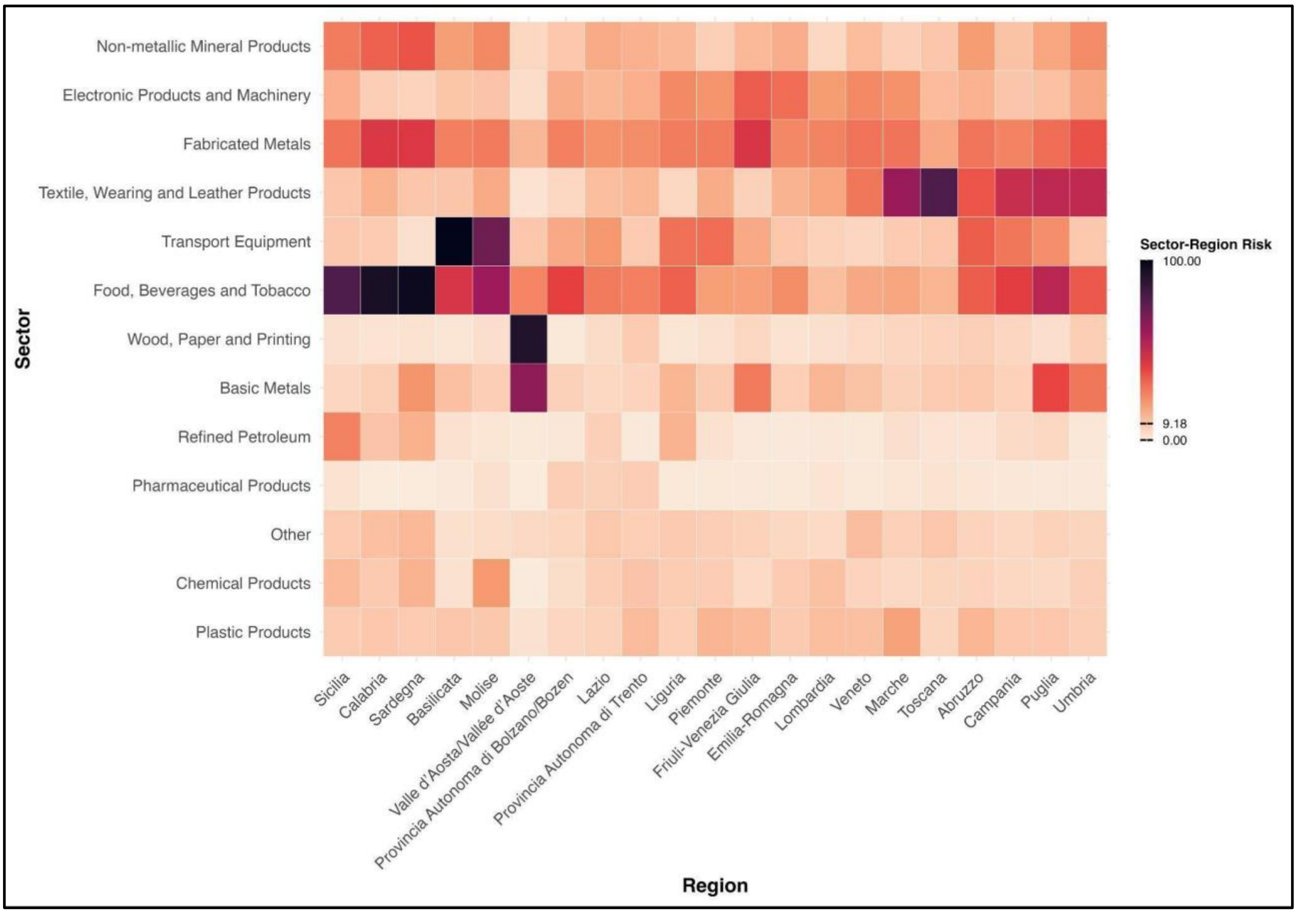

Figure 3: Heatmap of the regional-sectoral DRI for manufacturing in Italy (own elaboration)

To interpret the findings effectively, the analysis employed various visual tools, including heatmaps, geographical risk distribution maps, and bar plots. The heatmap of the weighted composite risk index (*Figure 3*) highlights the relative risk across sector-region pairs, identifying high-risk areas where focused interventions are crucial. The values represented in the heatmap are normalised, meaning they have been scaled to a common range (0 to 1) to allow for direct comparison across sectors and regions. The legend is segmented to display the quartiles of the data, clearly marking the distribution of risks from low to high.

Figure 4 shows the total risk of regions as the product of the risk of each region and the sum of the risk of each sector multiplied by the relative importance of that sector in that region, expressed as a weight. The map shows the Decarbonisation Risk Index (DRI) across Italian regions, highlighting significant variations in risk levels. Darker shades represent higher risk, with regions such as Sardinia, Lombardy, and Emilia-Romagna facing the greatest challenges. The legend displays quartiles of the data (minimum, median, and maximum), capturing the distribution of risk across the country.

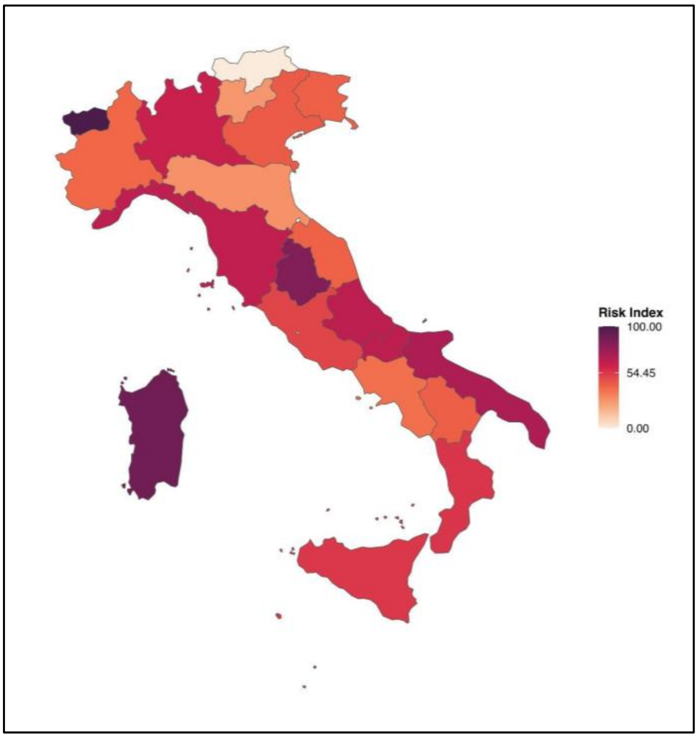

Figure 4: Map of regional DRI for manufacturing in Italy (median = 54.45, own elaboration)

It is worth remembering that the construction of the risk, vulnerability and exposure map of Italy integrate the "Response" indicator into the Regional Risk (R_r) component. This implies that the Italian maps will be slightly different from the colour codes of Italy in the European maps.

The analysis of the relative importance of sectors in a region, which represents the weight component in the final risk index, further illustrates that key industrial regions such as Lombardia, Emilia-Romagna, and Veneto have higher weights for sectors like Fabricated Metals, Electronic Products, and Transport Equipment, underscoring their economic significance. Decarbonisation efforts in these regions should prioritise these high-impact sectors to ensure that environmental goals are met without compromising economic stability. Some of these regions such as the industrial region of Lombardia in the north also benefit from diversity in their industrial portfolio which helps reduce their vulnerability to decarbonisation (*Figure 5*) compared to regions that rely heavily on only once industry. For example, in Sardegna and Sicilia, the elevated risks are primarily associated with the high exposure of Refined Petroleum sector to decarbonisation

(*Figure 6*), highlighting the critical need for targeted decarbonisation strategies in these regions.

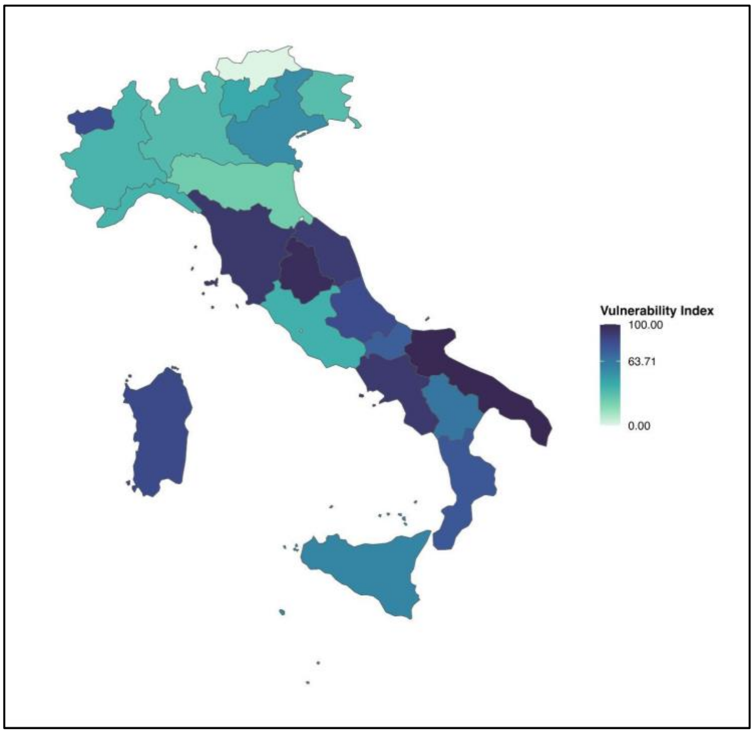

Figure 5: Map of regional vulnerability index for manufacturing in Italy (median = 63.71, own elaboration)

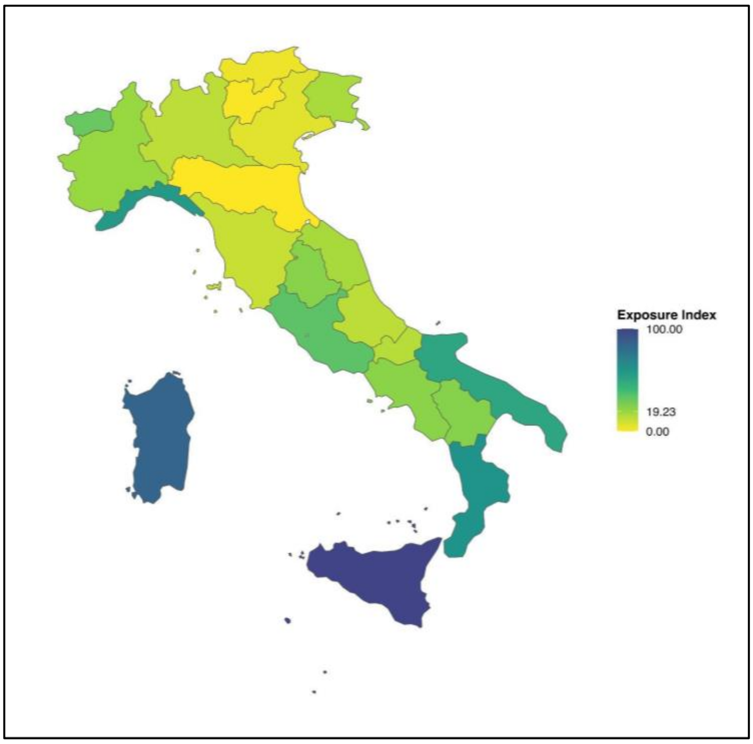

Figure 6: Map of regional exposure index for manufacturing in Italy (median = 19.23, own elaboration)

The significant presence of the Refined Petroleum industry in these areas suggests that decarbonisation efforts, if not managed carefully, could lead to substantial economic and social impacts, including potential job losses and the need for economic restructuring. Similarly, Lombardia, Italy's most industrialised region, faces considerable risk across multiple sectors, including Fabricated Metals and Basic Metals. The economy of Lombardia is intertwined with manufacturing sectors that are both energy-intensive and emission-heavy, underscoring the necessity for decarbonisation strategies that carefully balance environmental objectives with economic sustainability.

Toscana, another key region, displays high risks in the Textile, Wearing Apparel, and Leather Products sector, alongside significant risks in the Basic Metals and Fabricated Metals sectors. The textile sector, in particular, is characterised by high water and energy use, making it vulnerable to stricter environmental regulations. In Emilia-Romagna, the risks are notable across the Electronic Products and Fabricated Metals sectors. As a hub for high-tech manufacturing, this region faces unique challenges due to the high economic weight of these sectors. The Electronic Products sector, although less emission-intensive than heavy manufacturing, still faces substantial pressure to reduce its environmental footprint. This is particularly crucial given the global push towards greener supply chains and stricter environmental standards. Emilia-Romagna's decarbonisation strategy should therefore focus on innovation and technological upgrades, fostering public-private partnerships to drive the development and adoption of sustainable manufacturing practices. Veneto exhibits moderate to high risks across sectors such as Transport Equipment and Fabricated Metals. The automotive and machinery industries are central to Veneto's economy, and their decarbonisation will be pivotal in reducing the region's overall emissions. However, these industries face substantial challenges due to their deep-rooted reliance on complex supply chains and high energy consumption. Veneto's policy interventions should prioritise enhancing adaptive capacity through investments in green technologies, workforce retraining, and access to financial support for small and medium-sized enterprises (SMEs) involved in these sectors.

Regions in Southern Italy, including Calabria and Campania, also show significant risk profiles, particularly in sectors such as Food, Beverages, and Tobacco. While these regions are not as heavily industrialised as their Northern counterparts, their vulnerabilities stem from lower adaptive capacities, limited access to financing for green technologies, and economic dependencies on traditional manufacturing sectors. Decarbonisation policies in these areas should focus on enhancing resilience through investments in skills development, infrastructure improvements, and facilitating access to green financing options to support local businesses in transitioning towards sustainable practices.

Also Puglia faces significant decarbonisation challenges due to the presence of ILVA, one of Europe's largest and most polluting steel plants, which drives high risk in the Basic Metals sector. ILVA's operations, characterised by outdated technology and high emissions, not only impact the environment but also pose socio-economic risks, including potential job losses and economic instability if not managed carefully. Decarbonisation efforts must prioritise investments in cleaner steelmaking technologies, workforce retraining, and economic diversification to reduce dependency on heavy industry.

5 Decarbonisation Risk to EU Businesses

Similarly to the case of Italy, we can expand the analysis to all the Eu regions. We use the methodology explained earlier to calculate composite vulnerability, exposure, and risk for three key sectors of manufacturing, agriculture, and transportation.

5.1 Risk of EU Manufacturing to Decarbonisation

First, we focus on manufacturing as the main economic sector contributing to GHG emissions. *Figure 7* shows the vulnerability index for manufacturing businesses in the NUTS2 level EU regions. We can make two key observations. First, the median vulnerability index value is about 0.53 which means most of the EU regions have a moderate vulnerability to decarbonisation of the manufacturing sector. Second, the highest vulnerable regions are on the east and south of the EU which include regions with lower economic prosperity.

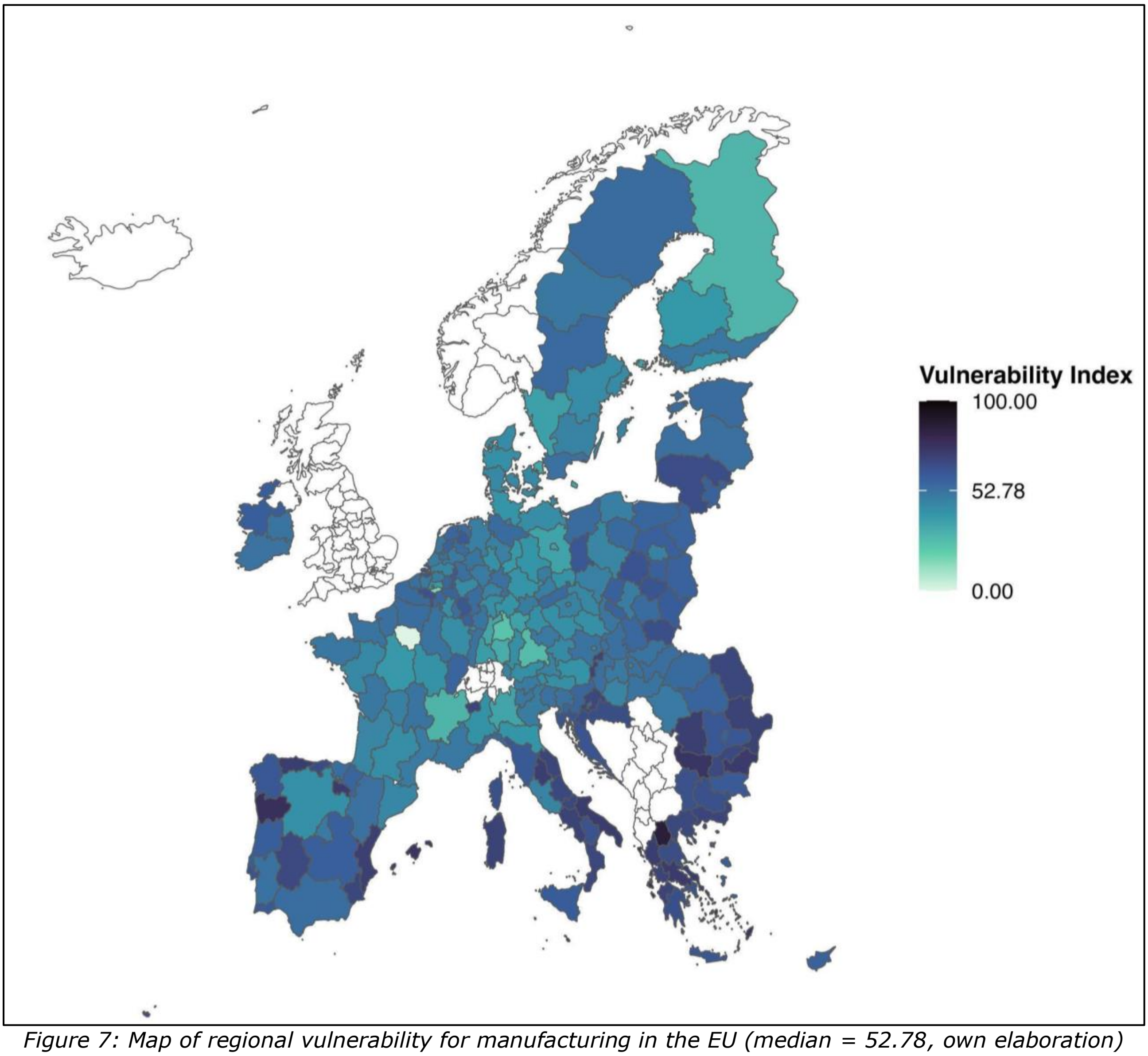

Figure 7: Map of regional vulnerability for manufacturing in the EU (median = 52.78, own elaboration)

We can also calculate the exposure of manufacturing sector across the EU regions (*Figure 8*). Here the high fossil fuel industries in Poland for example, contribute to the high exposure of the regions in the east.

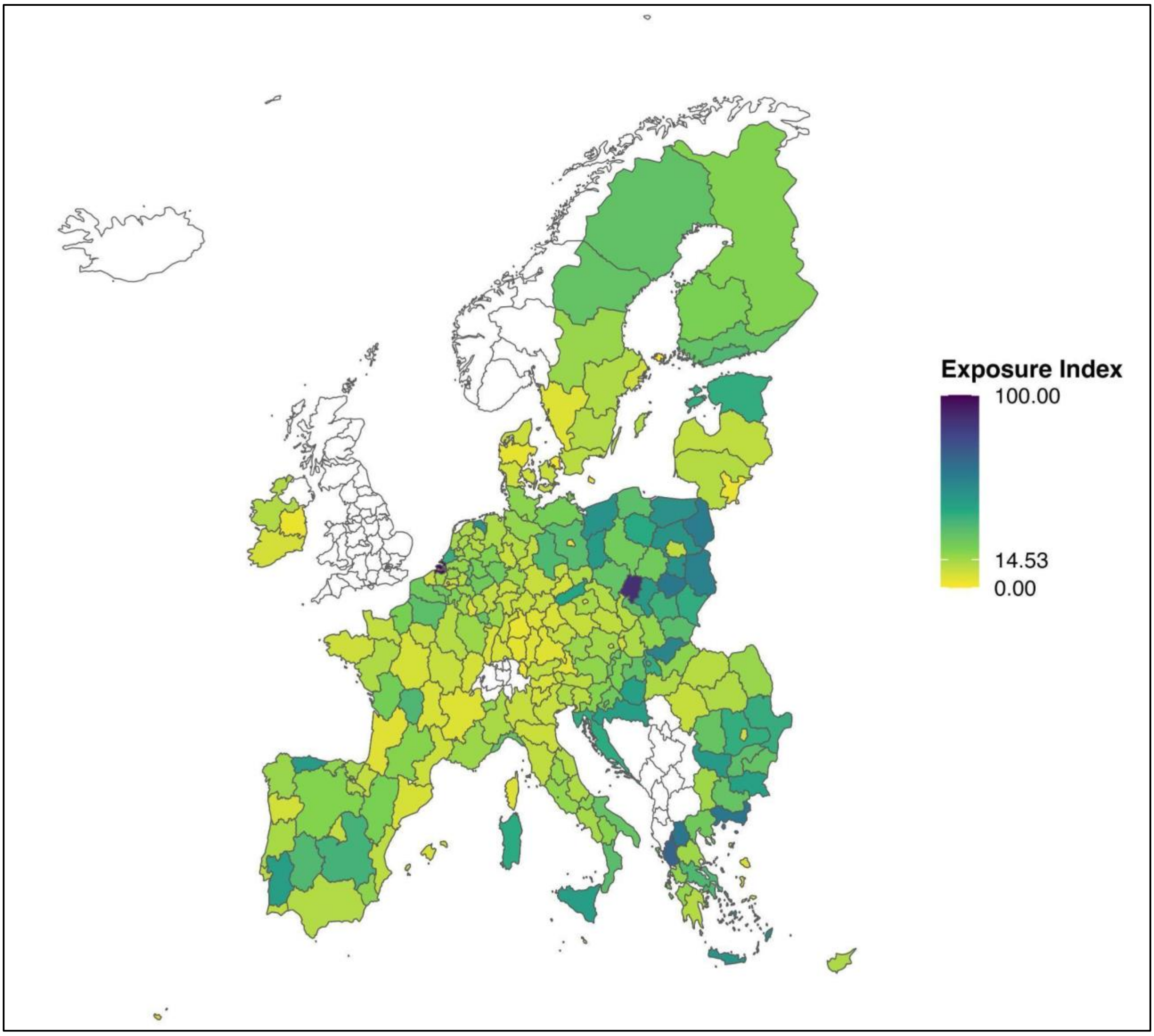

Figure 8: Map of regional exposure index for manufacturing in the EU (median = 14.53, own elaboration)

Finally, combining vulnerability and exposure, we can obtain the unified risk index of the manufacturing sector in the EU (*Figure 9*). While most of the EU regions are at a moderate risk of about 41%, the regions in the east specially are exposed to the highest risk of decarbonisation.

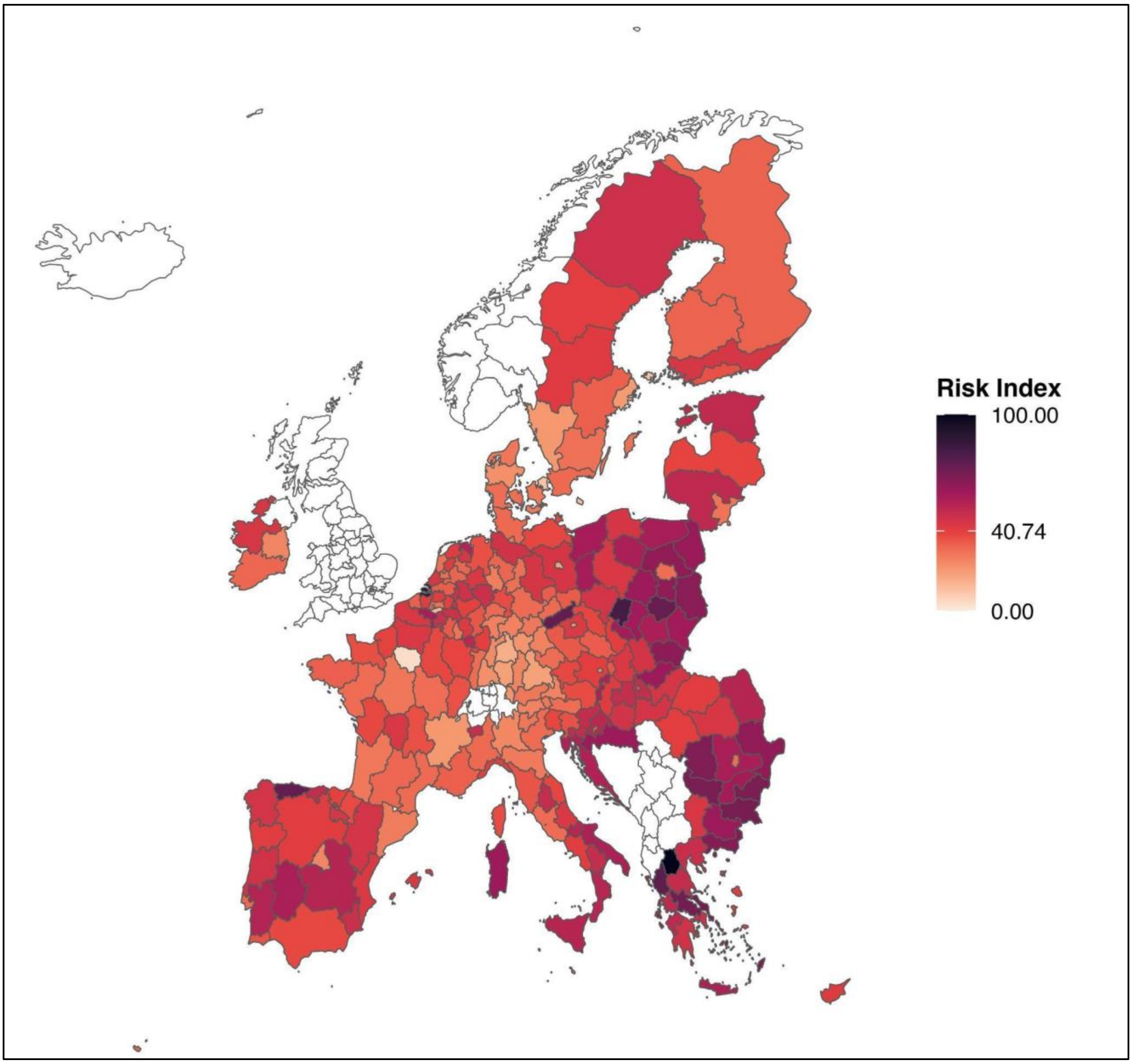

Figure 9: Map of regional DRI for manufacturing in the EU (median = 41.74, own elaboration)

5.2 Risk of EU Transportation to Decarbonisation

We start our analysis by focusing on vulnerability of transportation sector in the EU. *Figure 10* shows the vulnerability index for transportation businesses in the NUTS2 level EU regions. Compared to manufacturing, transportation businesses demonstrate a much lower vulnerability (the median value of 0.13 compared to 0.53). Also, regions with high vulnerability are scatter across the EU.

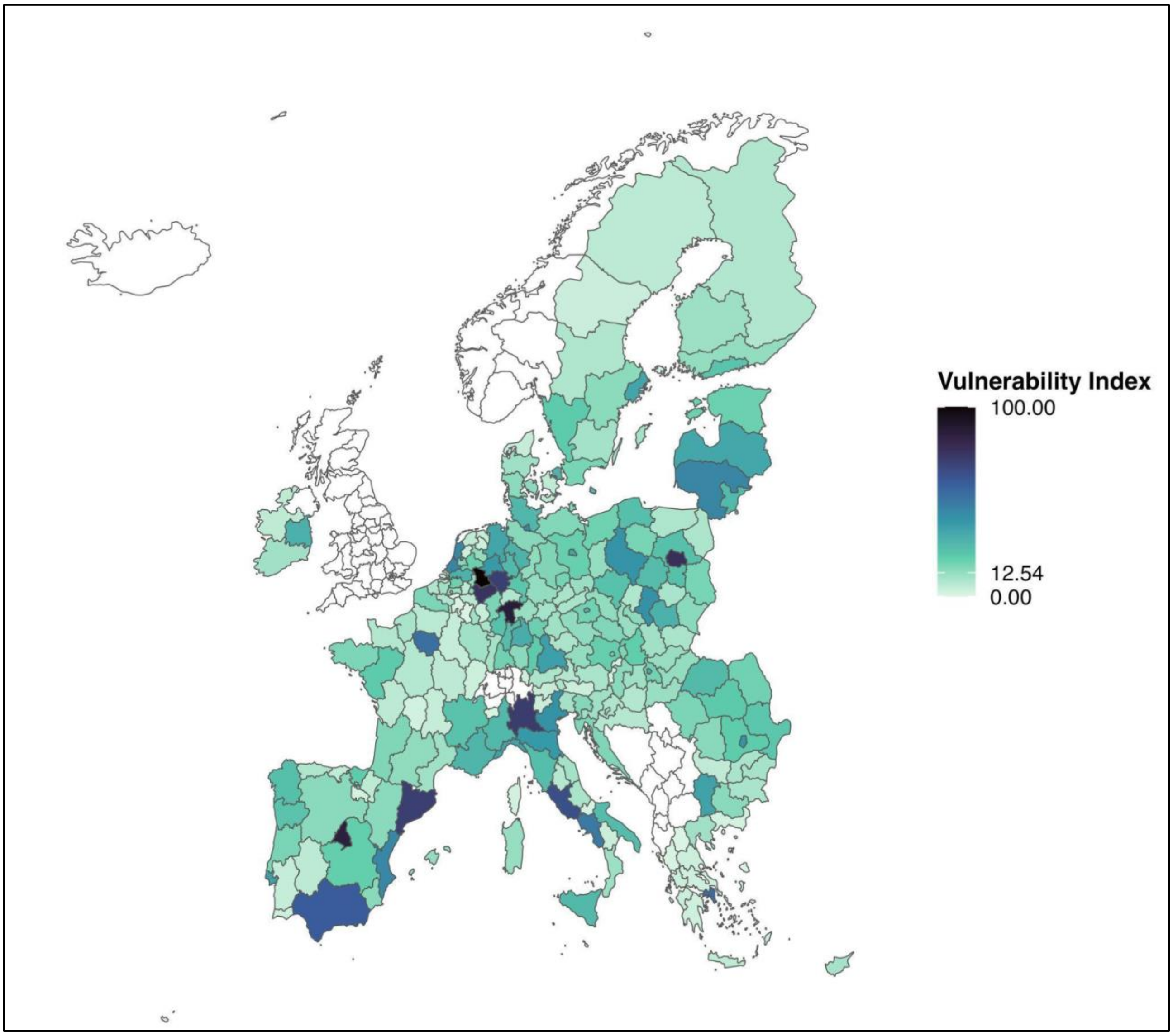

Figure 10: Map of regional vulnerability index for transportation in the EU (median = 12.54, own elaboration)

In terms of emissions, the transportation sector in most regions has also a low exposure.

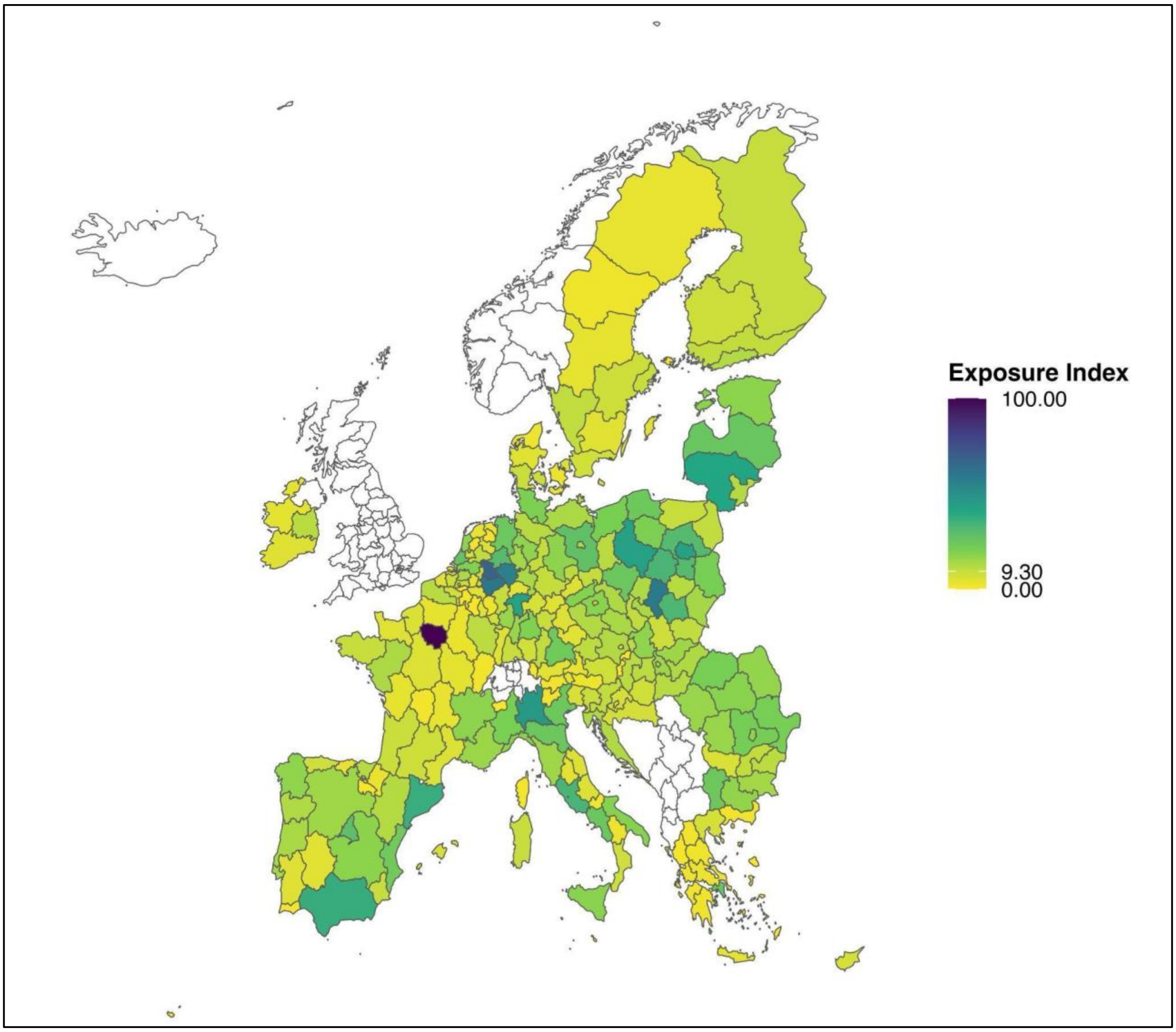

Figure 11: Map of regional exposure index for transportation in the EU (median = 9.30, own elaboration)

As a result, the unified decarbonisation risk index is relatively low in most of the EU regions (*Figure 12*).

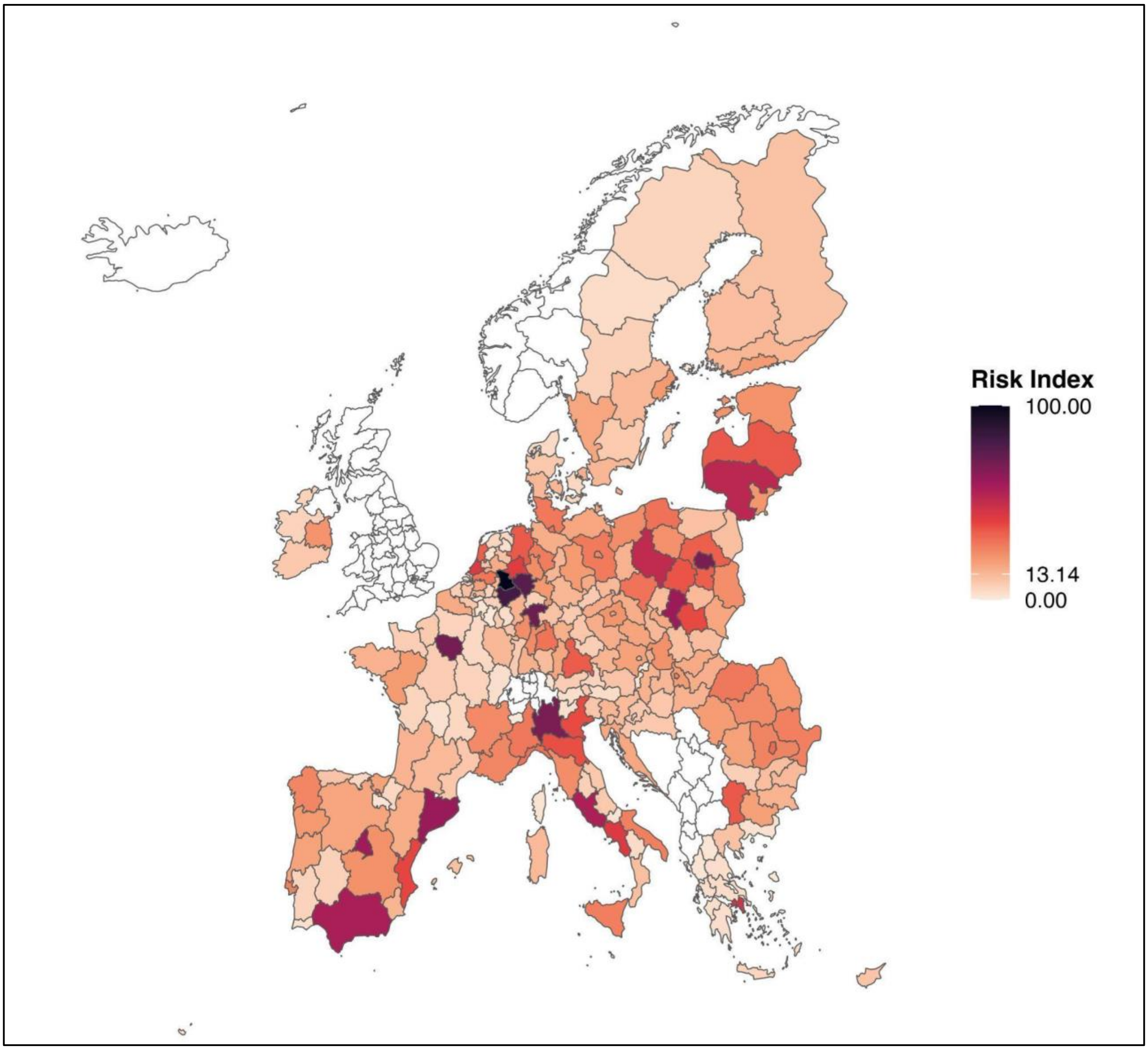

Figure 12: Map of regional DRI for transportation in the EU (median = 13.14, own elaboration)

5.3 Risk of EU Agriculture to Decarbonisation

The vulnerability of agriculture sector in the EU is shown in *Figure 13. It* shows the vulnerability index for agriculture businesses in the NUTS2 level EU regions are at a much lower level (the median value of 0.07 compared to 0.13 for transportation and 0.53 for manufacturing). Also, regions with high vulnerability are again on the east and south, representing the regions with high agricultural dependency.

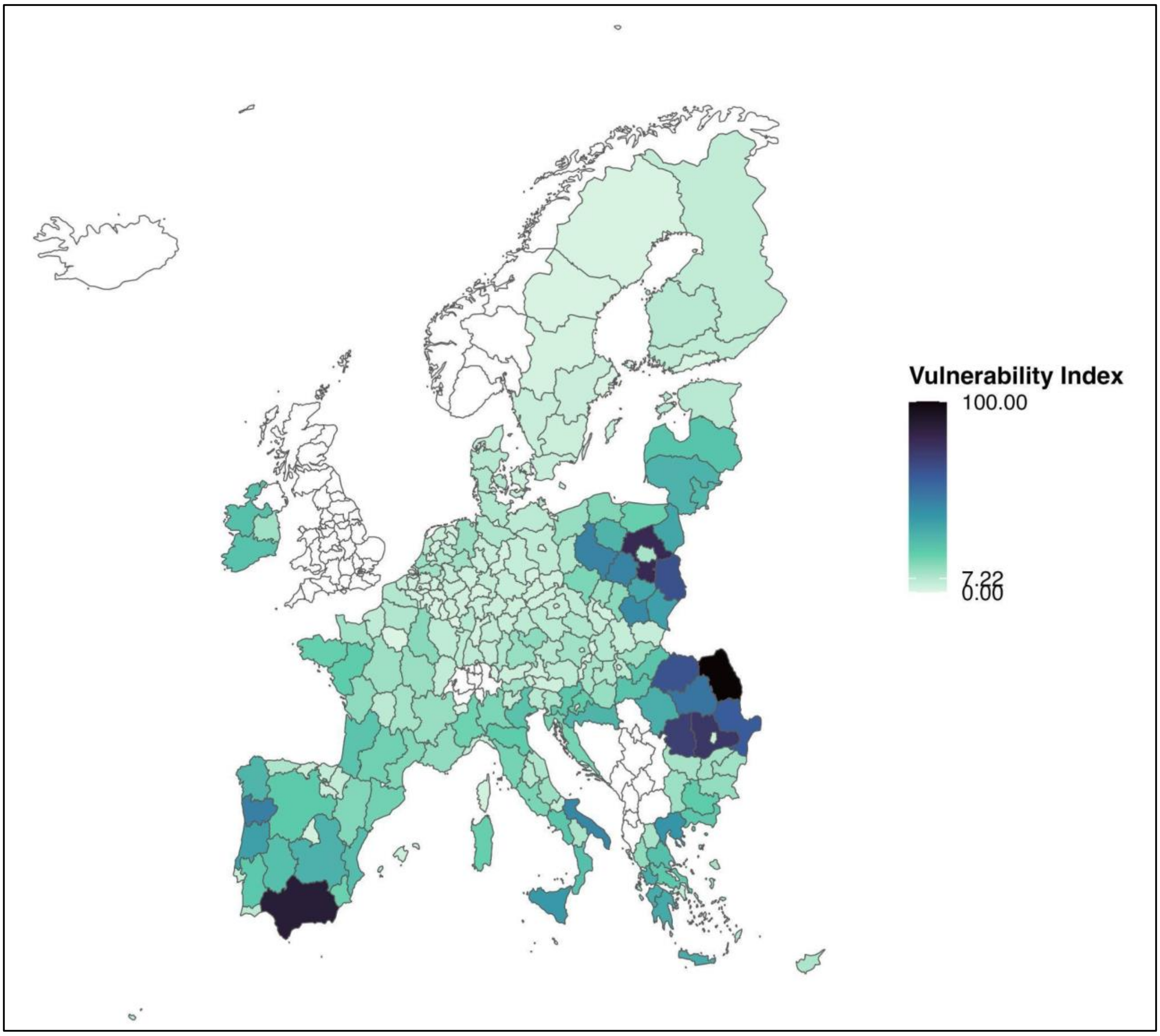

Figure 13: Map of regional vulnerability index for agriculture in the EU (median = 7.22, own elaboration)

In terms of exposure to emissions, the agriculture sector in most regions have relatively low values except for the eastern regions with high agricultural land use.

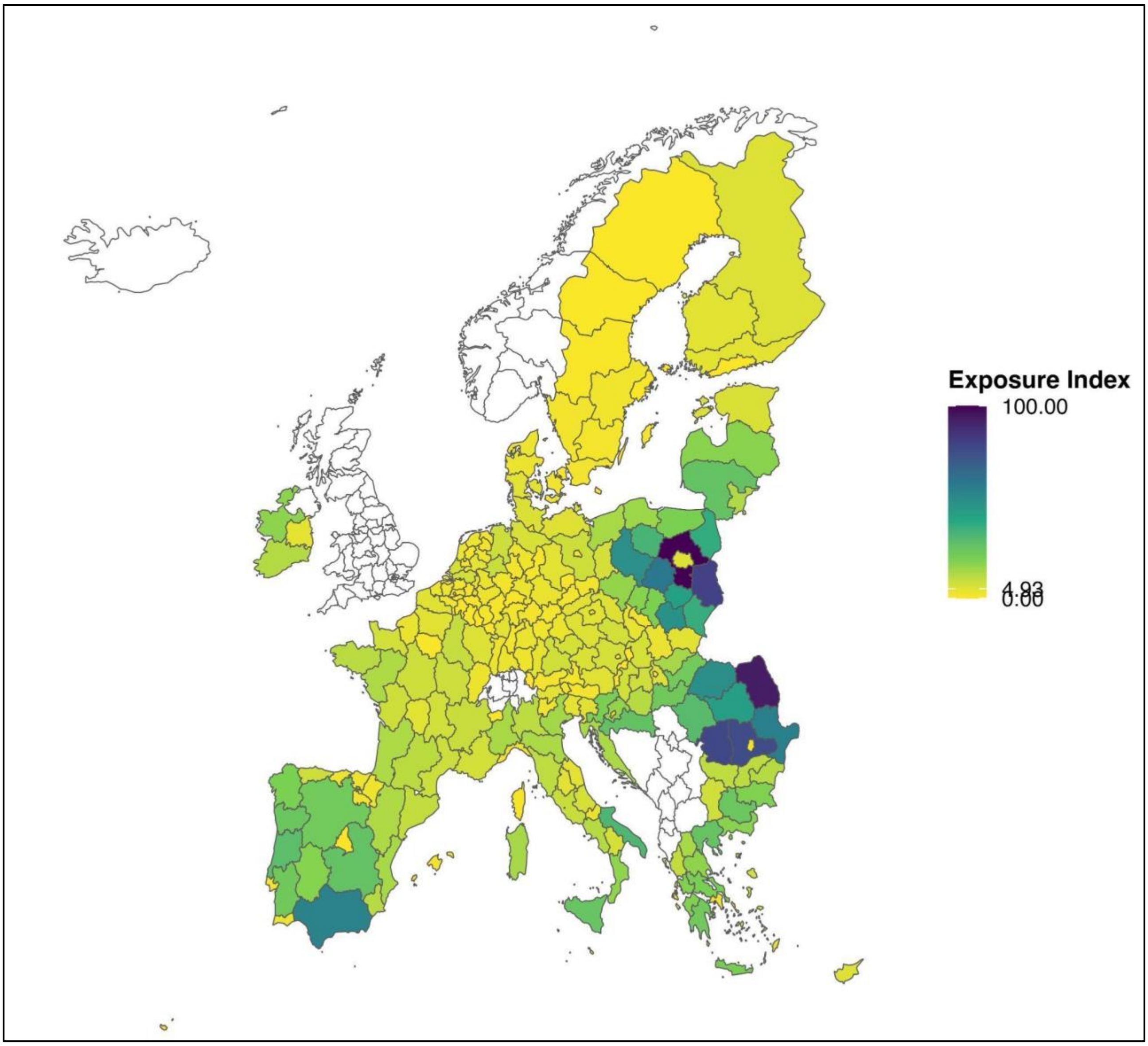

Figure 14: Map of regional exposure index for agriculture in the EU (median = 4.93, own elaboration)

This is also reflected in the decarbonisation risk index where eastern and some southern regions are highly at risk due to their dependency on agricultural activities.

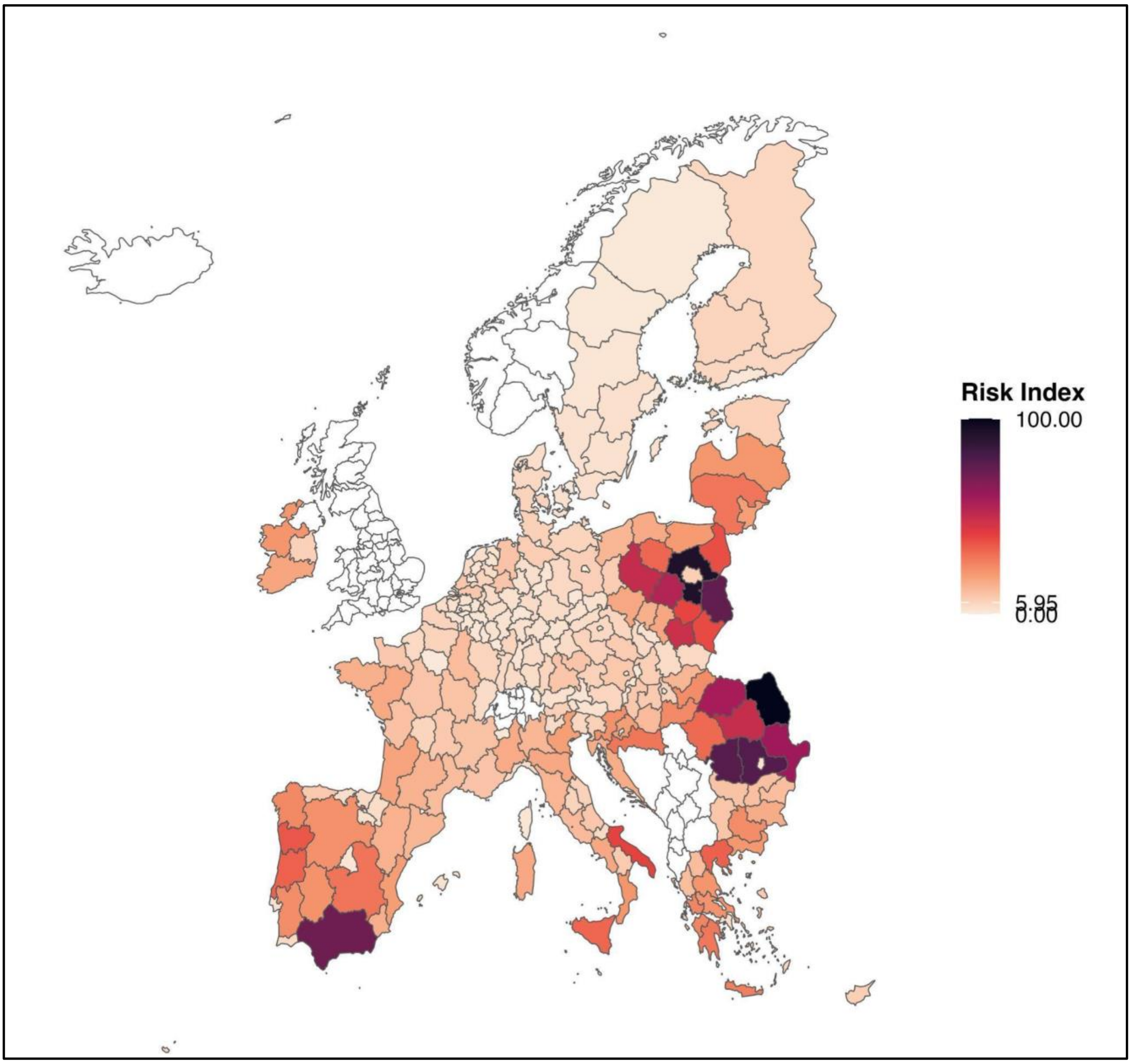

Figure 15: Map of regional DRI for agriculture in the EU (median = 5.95, own elaboration)

6 Conclusions and Limitations

This report presents a comprehensive analysis of the decarbonisation risks faced by the key economic sectors across the EU, focusing on the interplay between sectoral and regional vulnerabilities and exposures that together form a unified risk index.

The methodology introduced in this report is innovative on several fronts. First, by broadening the scope of the risk, we consider decarbonisation as a potential threat to the businesses which heavily relied on emission intensive energy sources for their operation or supply chain. Second, we built our risk assessment upon the most recent framework developed by IPCC AR6 as the key reference for global knowledge on climate change. Third, the composite indexes introduced in this report encompass main dimensions of business activities including energy, labour, supply chain, technology, and finance. This is a significant improvement compared to existing frameworks that mainly focus on employment as the driver of vulnerability in the green transition (McDowall et al., 2023).

Our analysis reveals several important patterns across the EU regions. First, decarbonisation vulnerability, exposure, and risk in the manufacturing sector is significantly higher than transportation and agriculture. This is chiefly due to (i) the prevalence of manufacturing sector in the EU as one of the highest developed regions in the world[1], (ii) the high energy and emission intensity of many manufacturing processes including refined petroleum and chemical products, and (iii) the high dependency of the EU industrial sector to trade with extra-EU countries. These factors together make the manufacturing sector in the EU a moderately vulnerable sector to decarbonisation.

Second, we observe a high vulnerability of businesses in manufacturing, transportation, and agriculture in the eastern regions of the EU (countries like Poland, Bulgaria, and Romania) and some southern regions (in Greece, Italy, and Spain). These regions are historically less developed than the rest of the EU and suffer from structural deficiencies. Nevertheless, the EU has allocated and spent considerable amounts of financial support in these regions which can potentially address some of the underlying vulnerabilities. Our analysis shows that such allocation of resources can be better guided using the vulnerability and risk index in combination with other socioeconomic and political considerations.

Third, the developed risk index (DRI) provides a detailed understanding of how decarbonisation pathways impact specific sectors and regions, revealing critical areas where targeted interventions are necessary. In the case of the Italian manufacturing sector, high-risk sectors such as Refined Petroleum, Basic Metals, and Fabricated Metals in regions like Sardegna, Sicilia, Lombardia, and Toscana highlight the need for strategic decarbonisation efforts that balance environmental objectives with economic stability.

[1] According to the ECB, industry, after services, has the second largest share of GDP in the Euro area (25%) https://www.ecb.europa.eu/mopo/eaec/html/index.en.html

The insights derived from this analysis are vital for policymakers and businesses to prioritise investments, foster technological innovation, and support workforce adaptation to ensure a just and efficient transition to a low-carbon economy.

Finally, we should highlight some of the limitations of our proposed framework. First, and most importantly, is the accessibility of data at the regional level. For our analysis we relied on Eurostat as the standard reference for all EU data. While the report uses data from Eurostat for a wide range of sectoral indicators, not all indicators are available for every region or sector. For instance, the data on financial investments are robust for the manufacturing and transportation sectors but more fragmented for agriculture and other service sectors. The lack of consistent data across all sectors introduces variability in the risk assessments, leading to potential underrepresentation of sectors where data is sparse. Although Eurostat provides a comprehensive repository of European data, its scope does not always capture the granular details necessary for constructing highly localised risk assessments. For example, indicators related to labour market dynamics (e.g., unemployment rates) and supply chain dependencies may not fully reflect regional complexities, especially in regions that rely heavily on external trade or are undergoing rapid economic shifts due to decarbonisation policies. The reliance on Eurostat also limits the inclusion of non-EU data sources that could provide additional context, especially for cross-border trade dependencies and global supply chains. Moreover, imputation was performed using sectoral averages or regional proxies to ensure that the data gaps did not overly bias the results. While this approach allowed for the construction of a more complete dataset, it inherently introduces a degree of uncertainty.

Although the risk index provides good insights into sectoral and regional vulnerabilities, it may not fully capture the complexity of interdependencies between sectors and regions. While there is room for improving data coverage, the report offers a reliable and actionable framework for policymakers and stakeholders to prioritise risk mitigation strategies.

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Appendix

EU Manufacturing Sector

Data preprocessing and normalization for exposure and vulnerabiltiy

Sectoral Risk

Sector Data: Manufacturing

Load data:

```r
library(tidyverse)
library(FactoMineR)
library(dplyr)
library(readxl)
library(eurostat)
library(giscoR)

EU_manuf_sectors <- read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory
Data/sectors/final/EU_aggregated_data_SECTORS.xlsx")

EU_manuf_regions <- read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory
Data/regions/final/EU_Manufacturing_REGION.xlsx")

EU_manuf_regions <- EU_manuf_regions |>
  mutate(ENER_final_cons = ENER_final_cons_region) |>
  select(-c(EMISS_GHG, NORM_GDPeuropercap, NORM_GDPmillion, NORM_POP,
            ENER_final_cons))
```

Data checks:

```r
any(is.na(EU_manuf_regions))

[1] FALSE

nuts2_map <- get_eurostat_geospatial(output_class = "sf", nuts_level = 2, year = 2021)
nuts2_map <- nuts2_map |>
  filter(CNTR_CODE %in% c("AT", "BE", "BG", "HR", "CY", "CZ", "DK", "EE", "FI", "FR", "DE",
                          "EL", "HU", "IE", "IT", "LV", "LT", "LU", "MT", "NL", "PL",
                          "PT", "RO", "SK", "SI", "ES", "SE")) |>
  filter(!grepl("ES7", NUTS_ID),
         !grepl("FRY", NUTS_ID),
         !grepl("PT2", NUTS_ID)) # Only continental EU27 countries

all(EU_manuf_regions$NUTS_ID %in% nuts2_map$NUTS_ID)

[1] FALSE

mismatches <- setdiff(EU_manuf_regions$NUTS_ID, nuts2_map$NUTS_ID)
mismatches

[1] "ES70" "PT20"
```

The risk of regions is the related to each NUTS 2 region of the EU across all NACE 2 manufacturing sectors:

$$Risk_{\square\square\square\square\square\square} = \sqrt{Exp_{\square\square\square\square\square\square} \times Vuln_{\square\square\square\square\square\square}}$$

The risk of sectors is the related to each NACE 2 manufacturing sector across all the EU NUTS 2 regions:

$$Risk_{\square\square\square\square\square\square} = \sqrt{Exp_{\square\square\square\square\square\square} \times Vuln_{\square\square\square\square\square\square}}$$

Vulnerability of sectors

Disaggregated vulnerability indicators for the manufacturing sector

We normalize the elements of the vulnerability index and we invert the values of the indicators that have a negative relationship with vulnerability, meaning that the higher the value, the lower the expected vulnerability.
Those are:

- RE share of energy consumption
- Size of the sector in terms of employment

- Average number of employees per enterprise per sector
- Average BERD per enterprise per sector
- Share of enterprises providing ICT training to employees per sector
- Investments in euros in tangible and intangible assets per enterprise per sector

```
EU_manuf_sectors <- EU_manuf_sectors |>
  group_by(Sector) |>
  summarise(across(where(is.numeric), \(x) sum(x, na.rm = TRUE)))

head(EU_manuf_sectors)

# A tibble: 6 × 16
  Sector EMISS_GHG ENER_fossil ENER_RE ENER_final_cons FIN_intanginv FIN_tanginv
  <chr>      <dbl>       <dbl>   <dbl>           <dbl>         <dbl>       <dbl>
1 Basic…    11.7         0.443 0.00226          130.          0.120        0.313
2 Chemi…     3.10        0.487 0.0250            49.4         0.202        0.172
3 Elect…     0.0944      0.322 0.0230             4.60        0.228        0.197
4 Fabri…     0.0293      0.322 0.0230             1.79        0.00598      0.0306
5 Food,…     0.178       0.513 0.0598             4.05        0.0117       0.0587
6 Non-m…     2.51        0.613 0.0684            18.3         0.0215       0.0698
# ℹ 9 more variables: LAB_totempl <dbl>, NORM_nofenterprs <dbl>,
#   SUPCH_export_euros <dbl>, SUPCH_export_share <dbl>,
#   SUPCH_import_euros <dbl>, SUPCH_import_share <dbl>, TECH_berd <dbl>,
#   LAB_npempl <dbl>, TECH_icttraining <dbl>

# Define the normalization function
normalize_min_max <- function(x, epsilon = 0.01) {
  min_value <- min(x, na.rm = TRUE)
  max_value <- max(x, na.rm = TRUE)
  norm_values <- (x - min_value) / (max_value - min_value)
  norm_values * (1 - 2 * epsilon) + epsilon
}

# Apply normalization to the numeric columns
manuf <- EU_manuf_sectors |>
  select(-EMISS_GHG, -NORM_nofenterprs) |>
  mutate(across(where(is.numeric), normalize_min_max))

# Columns to invert for vulnerability adjustment
m_col <- c("ENER_RE", "LAB_npempl", "LAB_totempl", "TECH_berd", "TECH_icttraining",
           "FIN_intanginv", "FIN_tanginv")

# Invert the specified columns
manuf <- manuf |>
  mutate(across(all_of(m_col), ~ 1 - .))

# Define groups of variables
var_groups <- list(
  Energy = c("ENER_final_cons", "ENER_fossil", "ENER_RE"),
  Labour = c("LAB_npempl", "LAB_totempl"),
  SupplyChain = c("SUPCH_export_euros", "SUPCH_export_share", "SUPCH_import_euros",
                  "SUPCH_import_share"),
  Technology = c("TECH_berd", "TECH_icttraining"),
  Finance = c("FIN_intanginv", "FIN_tanginv")
)

# Function to calculate weighted average using equal weights
weighted_avg_equal <- function(df, vars) {
  df_selected <- df |> select(all_of(vars)) |> drop_na()
  num_vars <- length(vars)
  equal_weights <- rep(1 / num_vars, num_vars)
  as.matrix(df_selected) %*% equal_weights
}

# Apply equal-weighted averages to each dimension
manuf_d <- manuf

for (group in names(var_groups)) {
  manuf_d[[group]] <- weighted_avg_equal(manuf_d, var_groups[[group]])
}

# Select the final columns to display
manuf_d <- manuf_d |>
  select(Sector, Energy, Labour, SupplyChain, Technology, Finance) |>
  mutate(across(c(Energy, Labour, SupplyChain, Technology, Finance), normalize_min_max))


head(manuf_d)

# A tibble: 6 × 6
  Sector        Energy[,1] Labour[,1] SupplyChain[,1] Technology[,1] Finance[,1]
```

```
  <chr>             <dbl>     <dbl>          <dbl>        <dbl>       <dbl>
1 Basic Metals      0.626     0.902          0.260        0.952       0.953
2 Chemical Pro…     0.626     0.934          0.108        0.729       0.960
3 Electronic P…     0.453     0.01           0.197        0.749       0.955
4 Fabricated M…     0.452     0.520          0.01         0.830       0.988
5 Food, Bevera…     0.606     0.199          0.0417       0.978       0.985
6 Non-metallic…     0.701     0.99           0.0315       0.830       0.983
```

`manuf_d` contains the normalized disaggregated vulnerability indicators for the manufacturing sector.

Aggregate vulnerability indicators for sectors into a unique index

```r
# Prepare the data by removing the 'Sector' and 'Country' columns
sectors <- manuf_d$Sector
countries <- manuf_d$Country
data <- manuf_d |>
  select(-Sector)

# Assign equal weights to each variable
num_variables <- ncol(data)
equal_weights <- rep(1 / num_variables, num_variables)

# Create composite scores for each row using equal weights
composite_scores <- as.matrix(data) %*% equal_weights

# Create a DataFrame for the vulnerability scores
V_s <- data.frame(
  Sector = sectors,
  Vulnerability = composite_scores
)

# Normalize the vulnerability scores using the min-max normalization
V_s$Vulnerability_norm <- normalize_min_max(V_s$Vulnerability)


head(V_s)

                            Sector Vulnerability Vulnerability_norm
1                     Basic Metals     0.7387680         0.94288931
2                Chemical Products     0.6712518         0.71525688
3 Electronic Products and Machinery     0.4727898         0.04613808
4                Fabricated Metals     0.5601419         0.34064766
5         Food, Beverages and Tobacco     0.5618454         0.34639105
6      Non-metallic Mineral Products     0.7069790         0.83571200
```

Keep it simple using equal weights for the vulnerability index.
`manuf_scores` contains the normalized aggregated vulnerability indicators for the manufacturing sector.

Exposure of sectors

```r
exp_manuf <- data.frame(Sector = EU_manuf_sectors$Sector,
                        EMISS_GHG = EU_manuf_sectors$EMISS_GHG)

# Select the necessary columns and rename EMISS_GHG to Exposure
exp_manuf <- exp_manuf |>
  select(Sector, EMISS_GHG) |>
  rename(Exposure = EMISS_GHG)

# Store the result in E_s and display the first few rows
E_s <- exp_manuf

E_s <- E_s |>
  mutate(Exposure_norm = normalize_min_max(Exposure))

head(E_s)

                            Sector    Exposure Exposure_norm
1                     Basic Metals 11.73877185    0.07031541
2                Chemical Products  3.09687137    0.02587492
3 Electronic Products and Machinery  0.09435746    0.01043466
4                Fabricated Metals  0.02929124    0.01010006
5         Food, Beverages and Tobacco  0.17800043    0.01086479
6      Non-metallic Mineral Products  2.51204939    0.02286750
```

Risk Index for Sectors:

```
# Merge the data frames by the "Entity" column
R_s <- V_s |>
  left_join(E_s, by = c("Sector"))

# Display the result
R_s <- R_s |>
  rename(Vulnerability_Sectors = Vulnerability_norm,
         Exposure_Sectors = Exposure_norm,
         Exposure_Sectors_notnorm = Exposure)

# R_s <- R_s |>
#   mutate(Exposure_Sectors = normalize_min_max(Exposure_Sectors))

# Geometric Mean Function to avoid zero issues
geometric_mean <- function(x, y) {
  sqrt(pmax(x, 0.01) * pmax(y, 0.01))
}

R_s <- R_s |>
  mutate(Risk_Sector = geometric_mean(Exposure_Sectors, Vulnerability_Sectors))


# Display the DataFrame with all Risk Indices
R_s <- R_s |>
  mutate(Risk_Sector_norm = normalize_min_max(Risk_Sector))

head(R_s)

                             Sector Vulnerability Vulnerability_Sectors
1                      Basic Metals     0.7387680            0.94288931
2                 Chemical Products     0.6712518            0.71525688
3 Electronic Products and Machinery     0.4727898            0.04613808
4                 Fabricated Metals     0.5601419            0.34064766
5       Food, Beverages and Tobacco     0.5618454            0.34639105
6     Non-metallic Mineral Products     0.7069790            0.83571200
  Exposure_Sectors_notnorm Exposure_Sectors Risk_Sector Risk_Sector_norm
1              11.73877185       0.07031541  0.25748718       0.39613870
2               3.09687137       0.02587492  0.13604122       0.20479364
3               0.09435746       0.01043466  0.02194163       0.02502320
4               0.02929124       0.01010006  0.05865630       0.08286927
5               0.17800043       0.01086479  0.06134709       0.08710876
6               2.51204939       0.02286750  0.13824127       0.20825994
```

Regional Risk

```
region <- EU_manuf_regions
```

```
# Apply normalization to the numeric columns
region_n <- region |>
  mutate(across(where(is.numeric), ~ normalize_min_max(.)))

region_n <- region_n |>
  select(-EMISS_GHG_intensity, -TECH_RDmillion)

# List of columns to adjust direction for vulnerability
m_col <- c("SUPCH_railnet", "TECH_RDeuropercap", "TECH_RDPERSperctotemp", "FIN_GFCP")

# Invert the specified columns by multiplying by -1
region_nf <- region_n |>
  mutate(across(all_of(m_col), ~ 1 - .))

Energy <- c("ENER_intensity")
Labour <- c("LAB_unemprate")
SupplyChain <- c("SUPCH_railnet")
Technology <- c("TECH_RDPERSperctotemp", "TECH_RDeuropercap")
Finance <- c("FIN_GFCP")

# Calculate the average for each dimension
region_d <- region_nf |>
  mutate(
    Energy = ENER_intensity,
    Labour = LAB_unemprate,
    SupplyChain = SUPCH_railnet,
    Technology = rowMeans(select(region_nf, all_of(Technology)), na.rm = TRUE),
    Finance = FIN_GFCP
  ) |>
  select(NUTS_ID, CNTR_CODE, NUTS_NAME, Energy,
         Labour, SupplyChain, Technology, Finance)
```

```
head(region_d)

# A tibble: 6 × 8
  NUTS_ID CNTR_CODE NUTS_NAME       Energy Labour SupplyChain Technology Finance
  <chr>   <chr>     <chr>            <dbl>  <dbl>       <dbl>      <dbl>   <dbl>
1 AT11    AT        Burgenland      0.0113 0.116        0.687      0.932   0.978
2 AT12    AT        Niederösterrei… 0.0112 0.102        0.687      0.845   0.906
3 AT13    AT        Wien            0.0110 0.283        0.687      0.478   0.857
4 AT21    AT        Kärnten         0.0112 0.123        0.687      0.771   0.957
5 AT22    AT        Steiermark      0.0113 0.0954       0.687      0.518   0.920
6 AT31    AT        Oberösterreich  0.0113 0.0680       0.687      0.681   0.902
```

`region_d` contains the normalized disaggregated vulnerability indicators for the Italian regions

Aggregate vulnerability indicators for regions into a unique index

```
# Function to calculate the vulnerability index for regional data using a specified weighting method
calculate_vulnerability_region <- function(data, method = "PCA") {

  # Extract NUTS_ID, CNTR_CODE, and NUTS_NAME columns for later use
  region_info <- data |> select(NUTS_ID, CNTR_CODE, NUTS_NAME)

  # Remove these columns from the data for PCA/Equal weighting calculation
  data <- data |> select(-NUTS_ID, -CNTR_CODE, -NUTS_NAME)

  # Select weights based on the chosen method
  if (method == "PCA") {
    # Perform PCA on the data (assuming it is normalized already)
    pca <- prcomp(data, center = FALSE, scale. = FALSE)

    # Extract loadings and explained variance
    loadings <- abs(pca$rotation[, 1:3])  # Use the first 3 principal components
    explained_variance <- pca$sdev^2 / sum(pca$sdev^2)

    # Calculate weights based on the first 3 components
    weights <- rowSums(loadings * explained_variance[1:3])
    normalized_weights <- weights / sum(weights)

  } else if (method == "Equal") {
    # Assign equal weights to each variable
    num_variables <- ncol(data)
    normalized_weights <- rep(1 / num_variables, num_variables)

  } else {
    stop("Invalid method. Choose 'PCA' or 'Equal'.")
  }

  # Calculate composite scores for each region
  composite_scores <- as.matrix(data) %*% normalized_weights

  # Create a DataFrame with the results
  vulnerability_scores <- region_info |>
    mutate(Vulnerability = composite_scores)

  # Return both vulnerability scores and the weights
  return(list(
    vulnerability_scores = vulnerability_scores,
    weights = normalized_weights
  ))
}

# Example usage with PCA weights
result_PCA <- calculate_vulnerability_region(region_d, method = "PCA")

# Extract and display vulnerability scores and weights for PCA
vulnerability_scores_PCA <- result_PCA$vulnerability_scores
weights_PCA <- result_PCA$weights

# Example usage with Equal weights
result_Equal <- calculate_vulnerability_region(region_d, method = "Equal")

# Extract and display vulnerability scores and weights for Equal method
vulnerability_scores_Equal <- result_Equal$vulnerability_scores
weights_Equal <- result_Equal$weights

# Normalize Vulnerability scores for Equal method
vulnerability_scores_Equal$Vulnerability_norm <-
  normalize_min_max(vulnerability_scores_Equal$Vulnerability)

# Store the normalized results in V_r and display the first few rows
```

```
V_r <- vulnerability_scores_Equal

head(V_r)

# A tibble: 6 × 5
  NUTS_ID CNTR_CODE NUTS_NAME        Vulnerability[,1] Vulnerability_norm[,1]
  <chr>   <chr>     <chr>                        <dbl>                  <dbl>
1 AT11    AT        Burgenland                   0.545                  0.525
2 AT12    AT        Niederösterreich             0.510                  0.460
3 AT13    AT        Wien                         0.463                  0.371
4 AT21    AT        Kärnten                      0.510                  0.459
5 AT22    AT        Steiermark                   0.446                  0.339
6 AT31    AT        Oberösterreich               0.470                  0.383
```

`region_scores` contains the normalized aggragted vulnerability indicators for the manufacturing sector.

Exposure of Regions

```
# Create a data frame with necessary columns from the region dataset
exp_region <- data.frame(
  NUTS_ID = region$NUTS_ID,
  CNTR_CODE = region$CNTR_CODE,
  NUTS_NAME = region$NUTS_NAME,
  EMISS_GHG_intensity = region$EMISS_GHG_intensity
)

# Select the necessary columns and rename EMISS_GHG_intensity to Exposure
exp_region <- exp_region |>
  select(NUTS_ID, CNTR_CODE, NUTS_NAME, EMISS_GHG_intensity) |>
  rename(Exposure = EMISS_GHG_intensity)

# Normalize the Exposure column
exp_region <- exp_region |>
  mutate(Exposure_norm = normalize_min_max(Exposure))

# Store the result in E_r and display the first few rows
E_r <- exp_region

# Display the first few rows of E_r
head(E_r)

  NUTS_ID CNTR_CODE        NUTS_NAME   Exposure Exposure_norm
1    AT11        AT       Burgenland 0.20761105    0.09232321
2    AT12        AT Niederösterreich 0.23052676    0.10313642
3    AT13        AT             Wien 0.06991976    0.02735094
4    AT21        AT          Kärnten 0.22298635    0.09957834
5    AT22        AT       Steiermark 0.26470293    0.11926310
6    AT31        AT   Oberösterreich 0.29741666    0.13469970
```

Adaptive response of regions

Potential integration of adaptive response of regions. Data missing. Potential idea for integration in the regional risk scores:

$$R_{\square,\square\square\square\square\square} = \sqrt{\frac{E_{\square\square\square\square} \times V_{\square\square\square\square}}{log(1 + Response)}}$$

$$R_{\square} = \sqrt{E_{\square\square\square\square} \times V_{\square\square\square\square}}$$

```
# Extension: data integration for adaptive response
```

Risk Index for Regions (without Adaptive Response):

```
# Remove exact duplicates from V_r and E_r
V_r <- V_r |>
  distinct(NUTS_ID, CNTR_CODE, NUTS_NAME, .keep_all = TRUE)

E_r <- E_r |>
  distinct(NUTS_ID, CNTR_CODE, NUTS_NAME, .keep_all = TRUE)

# Merge the data frames by the "NUTS_ID", "CNTR_CODE", and "NUTS_NAME" columns
R_r <- V_r |>
  left_join(E_r, by = c("NUTS_ID", "CNTR_CODE", "NUTS_NAME"))

R_r <- R_r |>
  rename(Vulnerability_Regions = Vulnerability_norm, Exposure_Regions = Exposure_norm)
```

```
# Display the merged data frame
head(R_r)

# A tibble: 6 × 7
  NUTS_ID CNTR_CODE NUTS_NAME  Vulnerability[,1] Vulnerability_Region…¹ Exposure
  <chr>   <chr>     <chr>                  <dbl>                  <dbl>    <dbl>
1 AT11    AT        Burgenland             0.545                  0.525   0.208
2 AT12    AT        Niederöst…             0.510                  0.460   0.231
3 AT13    AT        Wien                   0.463                  0.371   0.0699
4 AT21    AT        Kärnten                0.510                  0.459   0.223
5 AT22    AT        Steiermark             0.446                  0.339   0.265
6 AT31    AT        Oberöster…             0.470                  0.383   0.297
# ℹ abbreviated name: ¹Vulnerability_Regions[,1]
# ℹ 1 more variable: Exposure_Regions <dbl>
```

```
# Geometric Mean Function to avoid zero issues
geometric_mean <- function(x, y) {
  sqrt(pmax(x, 0.01) * pmax(y, 0.01))
}

R_r <- R_r |>
  mutate(Risk_Region = geometric_mean(Exposure_Regions, Vulnerability_Regions))

R_r <- R_r |>
  mutate(Risk_Region = normalize_min_max(Risk_Region))

head(R_r)

# A tibble: 6 × 8
  NUTS_ID CNTR_CODE NUTS_NAME  Vulnerability[,1] Vulnerability_Region…¹ Exposure
  <chr>   <chr>     <chr>                  <dbl>                  <dbl>    <dbl>
1 AT11    AT        Burgenland             0.545                  0.525   0.208
2 AT12    AT        Niederöst…             0.510                  0.460   0.231
3 AT13    AT        Wien                   0.463                  0.371   0.0699
4 AT21    AT        Kärnten                0.510                  0.459   0.223
5 AT22    AT        Steiermark             0.446                  0.339   0.265
6 AT31    AT        Oberöster…             0.470                  0.383   0.297
# ℹ abbreviated name: ¹Vulnerability_Regions[,1]
# ℹ 2 more variables: Exposure_Regions <dbl>, Risk_Region <dbl[,1]>

writexl::write_xlsx(R_r, "/Users/giocopp/Desktop/LOCALISED 7.1/DATA/Risk_Index_Region_Data.xlsx")
```

Calculate Combined Indexes:

We construct the combined total risk, vulnerability, and exposure indices for the aggregate manufacturing sector in the EU, weighted by the combination of the relative importance of the sectors in EU27 NUTS2 regions, following the formula:

$$R_{\square\square\square\square\square\square\square\square\square\square\square\square\square,r} = \sqrt{R_r \times \left(\sum_s w_{s,r} \cdot R_s\right)}$$

where:

$R_{\square\square\square\square\square\square\square\square\square\square\square\square\square,r}$ is the total risk for the manufacturing sector in region r,

- R_r is the region-level risk,
- $w_{s,r}$ is the weight of sector s in region r,
- R_s is the risk for sector s across all regions,
- $\sum_s$ is the summation over all sectors s in the manufacturing industry.

This indexes allows to have a snapshot of the measures across the EU regions based on their regional performances in terms of exposure (emissions), dimensions of vulnerability and their economic structure and specialization in the manufacturing sector. This allows to weight the sectoral scores in terms of exposure (emissions) and vulnerability dimensions by the relative importance of the sectors in the regions.

Adding weights to combine the Indexes: relative importance of sectors in regions:

Weights are calculated based on the relative employment of each sector within each region, according to the following formula:

$$w_{s,r} = \frac{Employment_{s,r}}{\sum_s \quad Employment_{s,r}}$$

where:

- $w_{s,r}$ is the normalized weight of sector s in region r,
- $Employment_{s,r}$ is the total number of person employed in sector s in region r,
- $\sum_s \quad Employment_{s,r}$ is the total employment across all sectors s in region r.

We demonstrate that relative employment is highly correlated to relative Gross Value Added (GVA) across sectors in regions in Italy:

```
library(tidyverse)

GVA <- readxl::read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/GVA.xlsx")
GVA <- GVA |>
  rename(Sector = combined_Sector)

final_composite_results <-  readxl::read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory
Data/composite_indexes_provisional.xlsx")

# Load the employment data, filtered for Italy (all regions)
combined_risk_df_italy <- final_composite_results %>%
  filter(CNTR_CODE == "IT") %>%
  select(Sector, NUTS_NAME, Normalized_Weight)

combined_risk_df_italy <- combined_risk_df_italy %>%
  select(Sector, NUTS_NAME, Normalized_Weight)

# Filter the weights dataset to keep Sector, Region, and Relative_GVA
GVA_italy <- GVA %>%
  select(Sector, Region, Relative_GVA)

# Merge the datasets using inner join for valid data across all regions in Italy
merged_data <- GVA %>%
  inner_join(combined_risk_df_italy, by = c("Sector", "Region" = "NUTS_NAME"))

# Step 1: Normalize Weight and Relative GVA across all of Italy
total_weight_italy <- sum(merged_data$Weight, na.rm = TRUE)
total_gva_italy <- sum(merged_data$Relative_GVA, na.rm = TRUE)

unique(merged_data$Region)

 [1] "Abruzzo"                           "Basilicata"
 [3] "Calabria"                          "Campania"
 [5] "Emilia-Romagna"                    "Friuli-Venezia Giulia"
 [7] "Lazio"                             "Liguria"
 [9] "Lombardia"                         "Marche"
[11] "Molise"                            "Piemonte"
[13] "Provincia Autonoma di Bolzano/Bozen" "Provincia Autonoma di Trento"
[15] "Puglia"                            "Sardegna"
[17] "Sicilia"                           "Toscana"
[19] "Umbria"                            "Veneto"

# Normalize both Weight and Relative GVA so their sum equals 1 across all regions
merged_data <- merged_data %>%
  mutate(Weight = Normalized_Weight,
         Relative_GVA = Relative_GVA)

# Create the scatterplot for all regions in Italy
GVA_Empl_corr_plot <- ggplot(merged_data, aes(x = Relative_GVA, y = Weight)) +
  geom_point(size = 1) +
  geom_smooth(aes()) +
  labs(
       x = "Relative GVA",
       y = "Relative Employment") +
  theme_minimal()

cor(merged_data$Relative_GVA, merged_data$Weight, use = "complete.obs")

[1] 0.8730282

ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/GVA_Empl_corr_plot.jpeg", plot = GVA_Empl_corr_plot, width = 10, height
= 7, dpi = 800)
```

Relative employment gives more importance to the “social” aspect rather to the “economic” one, following the classic “Just Transition” conceptual framework.

```
# Load necessary library
library(readxl)
library(dplyr)
```

```r
# Read the Excel file
weights <- read_excel("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/regions/raw/regions-energy/NORM_FINAL_nemployment.xlsx")

# Define the sector mapping
sector_mapping <- c(
  "Manufacture of food products" = "Food, Beverages and Tobacco",
  "Manufacture of beverages" = "Food, Beverages and Tobacco",
  "Manufacture of tobacco products" = "Food, Beverages and Tobacco",
  "Manufacture of textiles" = "Textile, Wearing and Leather Products",
  "Manufacture of wearing apparel" = "Textile, Wearing and Leather Products",
  "Manufacture of leather and related products" = "Textile, Wearing and Leather Products",
  "Manufacture of wood and of products of wood and cork, except furniture;
manufacture of articles of straw and plaiting materials" = "Wood, Paper and Printing",
  "Manufacture of paper and paper products" = "Wood, Paper and Printing",
  "Manufacture of coke and refined petroleum products" = "Refined Petroleum",
  "Manufacture of chemicals and chemical products" = "Chemical Products",
  "Manufacture of basic pharmaceutical products and pharmaceutical preparations" =
    "Pharmaceutical Products",
  "Manufacture of rubber and plastic products" = "Plastic Products",
  "Manufacture of other non-metallic mineral products" = "Non-metallic Mineral Products",
  "Manufacture of basic metals" = "Basic Metals",
  "Manufacture of fabricated metal products, except machinery and equipment" =
    "Fabricated Metals",
  "Manufacture of computer, electronic and optical products" =
    "Electronic Products and Machinery",
  "Manufacture of electrical equipment" = "Electronic Products and Machinery",
  "Manufacture of machinery and equipment n.e.c." = "Electronic Products and Machinery",
  "Manufacture of motor vehicles, trailers and semi-trailers" = "Transport Equipment",
  "Manufacture of other transport equipment" = "Transport Equipment",
  "Other manufacturing" = "Other"
)

# Convert sector_mapping into a data frame
mapping_df <- data.frame(
  original_sector = names(sector_mapping),
  new_sector = as.character(sector_mapping),
  stringsAsFactors = FALSE
)

# Reshape the dataset from wide to long format
weights_long <- weights |>
  gather(key = "sector", value = "employment", -NUTS_ID, -NUTS_NAME, -CNTR_CODE)

# Filter out 'Total Manufacturing' and 'Repair and installation of machinery and equipment'
weights_long <- weights_long |>
  filter(!(sector %in% c("Manufacturing",
                         "Repair and installation of machinery and equipment")))

# Join the long dataset with the sector mapping
weights_long <- weights_long |>
  left_join(mapping_df, by = c("sector" = "original_sector"))

# Filter out rows where new_sector is NA
weights_long <- weights_long |>
  filter(!is.na(new_sector))

# Aggregate the employment data by NUTS2 region and the new sectors
weights_aggregated <- weights_long |>
  group_by(NUTS_ID, NUTS_NAME, CNTR_CODE, new_sector) |>
  summarise(total_employment = sum(employment, na.rm = TRUE)) |>
  spread(key = new_sector, value = total_employment, fill = 0)

# View the aggregated dataset
head(weights_aggregated)

# A tibble: 6 × 16
# Groups:   NUTS_ID, NUTS_NAME, CNTR_CODE [6]
  NUTS_ID NUTS_NAME        CNTR_CODE `Basic Metals` `Chemical Products`
  <chr>   <chr>            <chr>              <dbl>               <dbl>
1 AT11    Burgenland       AT                 5276.                 374
2 AT12    Niederösterreich AT                 8476                 4759
3 AT13    Wien             AT                 5276.                1802
4 AT21    Kärnten          AT                 1093                  801
5 AT22    Steiermark       AT                10760                 1345
6 AT31    Oberösterreich   AT                12717                 6720
# ℹ 11 more variables: `Electronic Products and Machinery` <dbl>,
#   `Fabricated Metals` <dbl>, `Food, Beverages and Tobacco` <dbl>,
#   `Non-metallic Mineral Products` <dbl>, Other <dbl>,
#   `Pharmaceutical Products` <dbl>, `Plastic Products` <dbl>,
#   `Refined Petroleum` <dbl>, `Textile, Wearing and Leather Products` <dbl>,
#   `Transport Equipment` <dbl>, `Wood, Paper and Printing` <dbl>
```

```
# Save the aggregated dataset to a new Excel file if needed
writexl::write_xlsx(weights_aggregated, "/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/regions/raw/regions-energy/NORM_FINAL_aggregated.xlsx")

# Pivot the weights_aggregated data into long format
Empl_Weights <- weights_aggregated |>
  pivot_longer(
    cols = -c(NUTS_ID, NUTS_NAME, CNTR_CODE),
    names_to = "Sector",
    values_to = "Weight_Value"
  )

head(Empl_Weights)

# A tibble: 6 × 5
# Groups:   NUTS_ID, NUTS_NAME, CNTR_CODE [1]
  NUTS_ID NUTS_NAME  CNTR_CODE Sector                              Weight_Value
  <chr>   <chr>      <chr>     <chr>                                      <dbl>
1 AT11    Burgenland AT        Basic Metals                               5276.
2 AT11    Burgenland AT        Chemical Products                           374
3 AT11    Burgenland AT        Electronic Products and Machinery          2074
4 AT11    Burgenland AT        Fabricated Metals                          2363
5 AT11    Burgenland AT        Food, Beverages and Tobacco                3164
6 AT11    Burgenland AT        Non-metallic Mineral Products               855
```

Calculate Combined Risk, Exposure and Vulnerability Indexes:

```
# Step 1: Merge employment weights with sector data (R_s) to get sector risks, vulnerabilities, and exposures
sector_risk_with_weights <- Empl_Weights |>
  left_join(R_s, by = "Sector")

# Step 2: Normalize the weights for each region so that they sum to 1
# Set tolerance for small deviations from 1
tolerance <- 0.01

sector_risk_with_weights <- sector_risk_with_weights |>
  group_by(NUTS_ID) |>
  mutate(Total_Weight = sum(Weight_Value[Weight_Value > 0], na.rm = TRUE),
         Normalized_Weight = ifelse(Weight_Value > 0,
                                    Weight_Value / Total_Weight, 0)) |>
  ungroup()

# Step 3: Verify that the weights sum to 1 in each region (within a small tolerance)
weight_sum_check <- sector_risk_with_weights |>
  group_by(NUTS_ID) |>
  summarise(Total_Normalized_Weight = sum(Normalized_Weight, na.rm = TRUE))

# Step 4: Display regions where the total weight is not within tolerance
incorrect_weight_regions <- weight_sum_check |>
  filter(abs(Total_Normalized_Weight - 1) > tolerance)

# Step 5: Proceed only if no weights are incorrect
if (nrow(incorrect_weight_regions) > 0) {
  print("Warning: Some regions have weights that do not sum to 1 within tolerance.")
  print(incorrect_weight_regions)
} else {

  # Step 6: Calculate the weighted sums for Risk, Vulnerability, and Exposure for each region
  weighted_sums <- sector_risk_with_weights |>
    group_by(NUTS_ID, NUTS_NAME, CNTR_CODE) |>
    summarise(
      weighted_sum_risk = sum(Normalized_Weight * Risk_Sector, na.rm = TRUE),
      weighted_sum_vulnerability = sum(Normalized_Weight *
                                       Vulnerability_Sectors, na.rm = TRUE),
      weighted_sum_exposure = sum(Normalized_Weight *
                                  Exposure_Sectors_notnorm, na.rm = TRUE)
      # we use the not normalized exposure of sectors to calculate the weighted sum.
      # We will normalize the weighted sum directly
    ) |>
    ungroup()

  weighted_sums_norm <- weighted_sums |>
    mutate(Weighted_sum_risk = normalize_min_max(weighted_sum_risk),
           Weighted_sum_vulnerability = normalize_min_max(weighted_sum_vulnerability),
           Weighted_sum_exposure = normalize_min_max(weighted_sum_exposure))

  # Step 7: Merge the regional data from R_r (containing regional risk, vulnerability, and exposure data)
  combined_risk_data <- weighted_sums_norm |>
    left_join(R_r, by = c("NUTS_ID"))

  # Step 8: Calculate Composite Risk, Vulnerability, and Exposure using the provided formula
  combined_risk_data <- combined_risk_data |>
    mutate(
      Composite_Risk = sqrt(Risk_Region * Weighted_sum_risk),
      Composite_Vulnerability = sqrt(Vulnerability_Regions *
```

```
                                Weighted_sum_vulnerability),
      Composite_Exposure = sqrt(Exposure_Regions * Weighted_sum_exposure)
    )

  # Step 9: Select the final columns to display
  final_composite_results <- combined_risk_data |>
    left_join(sector_risk_with_weights, by = c("NUTS_ID")) |>
    select(Sector, NUTS_ID, NUTS_NAME, CNTR_CODE,
           Composite_Risk, Composite_Vulnerability, Composite_Exposure,
           Normalized_Weight, Total_Weight,
           Weighted_sum_risk, Weighted_sum_vulnerability, Weighted_sum_exposure,
           Risk_Region, Vulnerability_Regions, Exposure_Regions,
           Risk_Sector, Vulnerability_Sectors, Exposure_Sectors)
}

head(final_composite_results)

# A tibble: 6 × 18
  Sector   NUTS_ID NUTS_NAME CNTR_CODE Composite_Risk[,1] Composite_Vulnerabil…¹
  <chr>    <chr>   <chr>     <chr>                  <dbl>                  <dbl>
1 Basic M… AT11    Burgenla… AT                     0.444                  0.659
2 Chemica… AT11    Burgenla… AT                     0.444                  0.659
3 Electro… AT11    Burgenla… AT                     0.444                  0.659
4 Fabrica… AT11    Burgenla… AT                     0.444                  0.659
5 Food, B… AT11    Burgenla… AT                     0.444                  0.659
6 Non-met… AT11    Burgenla… AT                     0.444                  0.659
# ℹ abbreviated name: ¹Composite_Vulnerability[,1]
# ℹ 12 more variables: Composite_Exposure <dbl>, Normalized_Weight <dbl>,
#   Total_Weight <dbl>, Weighted_sum_risk <dbl>,
#   Weighted_sum_vulnerability <dbl>, Weighted_sum_exposure <dbl>,
#   Risk_Region <dbl[,1]>, Vulnerability_Regions <dbl[,1]>,
#   Exposure_Regions <dbl>, Risk_Sector <dbl>, Vulnerability_Sectors <dbl>,
#   Exposure_Sectors <dbl>

output_path <- file.path("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/",
                         "composite_indexes_provisional.xlsx")
writexl::write_xlsx(final_composite_results, output_path)

any(is.na(final_composite_results))

[1] FALSE
```

Final Dataset:

```
range(final_composite_results$Composite_Risk, na.rm = TRUE)

[1] 0.04413848 0.75372628

range(final_composite_results$Composite_Vulnerability, na.rm = TRUE)

[1] 0.07527753 0.91512426

range(final_composite_results$Composite_Exposure, na.rm = TRUE)

[1] 0.0182088 0.5546647

groups(final_composite_results)

list()

normalize_min_max_easy <- function(x) {
  min_value <- min(x, na.rm = TRUE)
  max_value <- max(x, na.rm = TRUE)
  norm_values <- (x - min_value) / (max_value - min_value)
}

# Normalize Indexes in the dataset apart from Exposure of Sectors
final_composite_results <- final_composite_results |>
  mutate(Composite_Risk = normalize_min_max_easy(Composite_Risk),
         Composite_Exposure = normalize_min_max_easy(Composite_Exposure),
         Composite_Vulnerability = normalize_min_max_easy(Composite_Vulnerability),
         Vulnerability_Regions = normalize_min_max_easy(Vulnerability_Regions),
         Exposure_Regions = normalize_min_max_easy(Exposure_Regions),
         Risk_Region = normalize_min_max_easy(Risk_Region),
         Risk_Sector = normalize_min_max_easy(Risk_Sector))

final_composite_results <- final_composite_results |>
  select(Sector, NUTS_ID, NUTS_NAME, CNTR_CODE,
           Composite_Risk, Composite_Vulnerability, Composite_Exposure,
           Normalized_Weight,
           Risk_Region, Vulnerability_Regions, Exposure_Regions,
           Risk_Sector, Vulnerability_Sectors, Exposure_Sectors)
```

```
head(final_composite_results)

# A tibble: 6 × 14
  Sector    NUTS_ID NUTS_NAME CNTR_CODE Composite_Risk[,1] Composite_Vulnerabil…¹
  <chr>     <chr>   <chr>     <chr>                  <dbl>                  <dbl>
1 Basic M… AT11    Burgenla… AT                     0.564                  0.695
2 Chemica… AT11    Burgenla… AT                     0.564                  0.695
3 Electro… AT11    Burgenla… AT                     0.564                  0.695
4 Fabrica… AT11    Burgenla… AT                     0.564                  0.695
5 Food, B… AT11    Burgenla… AT                     0.564                  0.695
6 Non-met… AT11    Burgenla… AT                     0.564                  0.695
# ℹ abbreviated name: ¹Composite_Vulnerability[,1]
# ℹ 8 more variables: Composite_Exposure <dbl>, Normalized_Weight <dbl>,
#   Risk_Region <dbl[,1]>, Vulnerability_Regions <dbl[,1]>,
#   Exposure_Regions <dbl>, Risk_Sector <dbl>, Vulnerability_Sectors <dbl>,
#   Exposure_Sectors <dbl>
```

Additional Indexes: Risk of sectors in regions

Notice that the Composite Indexes are aggregated measures of risk, exposure and vulnerability at the regional level, according to the structure the manufacturing sectors in the regions of reference. However, these aggregate measures do not allow to understand the risk of a specific sector in a specific region.

The Sector-Region Risk Index is calculated as follow:

$$R_{sector,region} = w_{s,r} \times \sqrt{R_{sector} \cdot R_{region}}$$

where:

- $R_{sector,region}$ is the risk for sector s in region r,
- $w_{s,r}$ is the normalized weight of sector s in region r,
- R_{sector} is the overall risk for sector s,
- R_{region} is the overall risk for region r.

```
sector_region_risk <- sector_risk_with_weights |>
  left_join(R_r |> select(-CNTR_CODE, -NUTS_NAME), by = "NUTS_ID") |>
  mutate(Sector_Region_Risk_raw = sqrt(Risk_Sector * Risk_Region)) |>
  mutate(Sector_Region_Risk = Normalized_Weight * Sector_Region_Risk_raw) |>
  mutate(Sector_Region_Risk = normalize_min_max_easy(Sector_Region_Risk)) |>
  select(Sector, NUTS_ID, Risk_Sector, Risk_Region, Sector_Region_Risk_raw, Normalized_Weight, Sector_Region_Risk)

head(sector_region_risk)

# A tibble: 6 × 7
  Sector                NUTS_ID Risk_Sector Risk_Region[,1] Sector_Region_Risk_r…¹
  <chr>                 <chr>         <dbl>           <dbl>                  <dbl>
1 Basic Metals          AT11         0.257           0.242                  0.250
2 Chemical Products     AT11         0.136           0.242                  0.182
3 Electronic Product…   AT11         0.0219          0.242                  0.0729
4 Fabricated Metals     AT11         0.0587          0.242                  0.119
5 Food, Beverages an…   AT11         0.0613          0.242                  0.122
6 Non-metallic Miner…   AT11         0.138           0.242                  0.183
# ℹ abbreviated name: ¹Sector_Region_Risk_raw[,1]
# ℹ 2 more variables: Normalized_Weight <dbl>, Sector_Region_Risk <dbl[,1]>

# Importantly, when we plot the country heatmaps, we have to normalize the Sector-Region Risk Index by country, to see,
within that country, what is the distribution of risk among sectors and regions.

sector_region_risk_join <- sector_region_risk |>
  select(Sector, NUTS_ID, Sector_Region_Risk)

final_composite_results <- final_composite_results |>
  left_join(sector_region_risk_join, by = c("NUTS_ID", "Sector"))

c <- c("Composite_Risk", "Composite_Vulnerability", "Composite_Exposure",
       "Normalized_Weight", "Risk_Region", "Vulnerability_Regions",
       "Exposure_Regions", "Risk_Sector", "Vulnerability_Sectors",
       "Exposure_Sectors", "Sector_Region_Risk")

final_composite_results <- final_composite_results %>%
  mutate(across(all_of(c), ~ round(. * 100, 2)))

# Verify the results
head(final_composite_results)

# A tibble: 6 × 15
  Sector    NUTS_ID NUTS_NAME CNTR_CODE Composite_Risk[,1] Composite_Vulnerabil…¹
  <chr>     <chr>   <chr>     <chr>                  <dbl>                  <dbl>
1 Basic M… AT11    Burgenla… AT                      56.4                   69.5
```

```
2 Chemica… AT11    Burgenla… AT                      56.4                 69.5
3 Electro… AT11    Burgenla… AT                      56.4                 69.5
4 Fabrica… AT11    Burgenla… AT                      56.4                 69.5
5 Food, B… AT11    Burgenla… AT                      56.4                 69.5
6 Non-met… AT11    Burgenla… AT                      56.4                 69.5
# ℹ abbreviated name: ¹Composite_Vulnerability[,1]
# ℹ 9 more variables: Composite_Exposure <dbl>, Normalized_Weight <dbl>,
#   Risk_Region <dbl[,1]>, Vulnerability_Regions <dbl[,1]>,
#   Exposure_Regions <dbl>, Risk_Sector <dbl>, Vulnerability_Sectors <dbl>,
#   Exposure_Sectors <dbl>, Sector_Region_Risk <dbl[,1]>

output_path <- file.path("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/",
                         "EU_Manufactory_Data.xlsx")
writexl::write_xlsx(final_composite_results, output_path)

head(final_composite_results)

# A tibble: 6 × 15
  Sector   NUTS_ID NUTS_NAME CNTR_CODE Composite_Risk[,1] Composite_Vulnerabil…¹
  <chr>    <chr>   <chr>     <chr>                  <dbl>                  <dbl>
1 Basic M… AT11    Burgenla… AT                      56.4                 69.5
2 Chemica… AT11    Burgenla… AT                      56.4                 69.5
3 Electro… AT11    Burgenla… AT                      56.4                 69.5
4 Fabrica… AT11    Burgenla… AT                      56.4                 69.5
5 Food, B… AT11    Burgenla… AT                      56.4                 69.5
6 Non-met… AT11    Burgenla… AT                      56.4                 69.5
# ℹ abbreviated name: ¹Composite_Vulnerability[,1]
# ℹ 9 more variables: Composite_Exposure <dbl>, Normalized_Weight <dbl>,
#   Risk_Region <dbl[,1]>, Vulnerability_Regions <dbl[,1]>,
#   Exposure_Regions <dbl>, Risk_Sector <dbl>, Vulnerability_Sectors <dbl>,
#   Exposure_Sectors <dbl>, Sector_Region_Risk <dbl[,1]>
```

Visualizations Manufacturing

EU Maps - Manufacturing

Maps show the total risk, vulnerability, and exposure indices for the aggreagte manufacturing sector in the EU, weighted by the combination of the relative importance of the sectors in EU27 NUTS2 regions, following the formula:

$$R_{manufacturing,r} = \sqrt{R_r \times \left(\sum_s \quad w_{s,r} \cdot R_s \right)}$$

where:

- $R_{manufacturing,r}$ is the total risk for the manufacturing sector in region r,
- R_r is the region-level risk,
- $w_{s,r}$ is the weight of sector s in region r, namely the total employment in sector s in region r divided by the total employment in the manufacturing industry in region r,
- R_s is the risk for sector s across all regions,
- $\sum_s$ is the summation over all sectors s in the manufacturing industry.

Objective: The goal is to assess the risk levels of regions based on their own characteristics and sectoral compositions. The Composite_Risk allows to compare regions based on their inherent risk levels without considering their relative importance to the national economy.

```
# Load necessary libraries
library(sf)
library(dplyr)
library(ggplot2)
library(readxl)
library(eurostat)
library(tidyverse)

output_path <- file.path("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/", "EU_Manufactory_Data.xlsx")
final_composite_results <- readxl::read_xlsx(output_path)

# Step 1: Get the NUTS2 shapefile for Europe from Eurostat
nuts2_map <- get_eurostat_geospatial(output_class = "sf", resolution = "10", nuts_level = 2, year = 2021)

# Step 2: Filter to include only EU27 countries based on CNTR_CODE
eu_nuts2_map <- nuts2_map %>%
  filter(CNTR_CODE %in% c("AT", "BE", "BG", "HR", "CY", "CZ", "DK", "EE", "FI", "FR", "DE",
                          "EL", "HU", "IE", "IT", "LV", "LT", "LU", "MT", "NL", "PL",
                          "PT", "RO", "SK", "SI", "ES", "SE"))

# Step 3: Filter out non-continental regions (like islands)
# Use the bounding box to exclude regions with low latitude (e.g., Canary Islands)
# You can adjust the latitude and longitude cutoffs as needed
continental_eu_nuts2_map <- nuts2_map %>%
  filter(!grepl("ES7", NUTS_ID),
         !grepl("FRY", NUTS_ID),
         !grepl("PT2", NUTS_ID),
         !grepl("TR", NUTS_ID))

map_data <- continental_eu_nuts2_map %>%
  left_join(final_composite_results, by = "NUTS_ID")

any(is.na(map_data))

[1] TRUE
```

Prepare plots:

```
# Load required libraries
library(ggplot2)
library(dplyr)
library(sf)
library(RColorBrewer)
library(viridis)
library(cowplot)


### Risk

min <- min(map_data$Composite_Risk, na.rm = TRUE)
median <- median(map_data$Composite_Risk, na.rm = TRUE)
max <- max(map_data$Composite_Risk, na.rm = TRUE)
```

```
Risk_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Risk)) +
  scale_fill_viridis_c(
    option = "rocket",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Risk Index"  # Add legend title
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )

### Exposure

min <- min(map_data$Composite_Exposure, na.rm = TRUE)
median <- median(map_data$Composite_Exposure, na.rm = TRUE)
max <- max(map_data$Composite_Exposure, na.rm = TRUE)

Exposure_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Exposure)) +
  scale_fill_viridis_c(
    option = "viridis",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Exposure Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )


### Vulnerability

min <- min(map_data$Composite_Vulnerability, na.rm = TRUE)
median <- median(map_data$Composite_Vulnerability, na.rm = TRUE)
max <- max(map_data$Composite_Vulnerability, na.rm = TRUE)

Vulnerability_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Vulnerability)) +
  scale_fill_viridis_c(
    option = "mako",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Vulnerability Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )
```

Save and print:

```
Risk_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Risk_map_MANUF_EU.jpeg", Risk_map, width = 10, height = 7, dpi = 800)

Exposure_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Exposure_map_MANUF_EU.jpeg", Exposure_map, width = 10, height = 7, dpi =
800)

Vulnerability_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Vulnerability_map_MANUF_EU.jpeg", Vulnerability_map, width = 10, height
= 7, dpi = 800)
```

Italian Maps

Prepare data:

Add Response:

```
# # Load AR_r dataset and normalize Response
# AR_r <- readxl::read_xlsx("/Users/giocopp/Desktop/AR_r.xlsx")
# Empl_Weights <- readxl::read_xlsx("/Users/giocopp/Desktop/Empl_Weights")
# R_s <- readxl::read_xlsx("/Users/giocopp/Desktop/Risk_Sector.xlsx")
# R_r <- readxl::read_xlsx("/Users/giocopp/Desktop/Risk_Region.xlsx")
#
# normalize_min_max <- function(x, epsilon = 0.01) {
#   min_value <- min(x, na.rm = TRUE)
#   max_value <- max(x, na.rm = TRUE)
#   norm_values <- (x - min_value) / (max_value - min_value)
#   norm_values * (1 - 2 * epsilon) + epsilon
# }
#
# AR_r <- AR_r |>
#   rename(NUTS_NAME = Entity) |>
#   mutate(Response = normalize_min_max(Adaptive_Response))
#
# # Function to calculate geometric mean with Response
# geometric_mean_with_response <- function(x, y, response) {
#   sqrt(pmax(x, 0.01) * pmax(y, 0.01) / log(1 + pmax(response, 0.01)))
# }
#
# # Step 1: Filter for Italy and merge employment weights with sector data (R_s) to get sector risks
# sector_risk_with_weights <- Empl_Weights |>
#   left_join(R_s, by = "Sector") |>
#   filter(CNTR_CODE == "IT")
#
# # Step 2: Normalize the weights for each region so that they sum to 1
# sector_risk_with_weights_it <- sector_risk_with_weights |>
#   group_by(NUTS_ID) |>
#   mutate(Total_Weight = sum(Weight_Value[Weight_Value > 0], na.rm = TRUE),
#          Normalized_Weight = ifelse(Weight_Value > 0,
#                                     Weight_Value / Total_Weight, 0)) |>
#   ungroup()
#
# # Step 3: Calculate the weighted sums for Risk, Vulnerability, and Exposure for each region
# weighted_sums <- sector_risk_with_weights_it |>
#   group_by(NUTS_ID, NUTS_NAME, CNTR_CODE) |>
#   summarise(
#     weighted_sum_risk = sum(Normalized_Weight * Risk_Sector, na.rm = TRUE),
#     weighted_sum_vulnerability = sum(Normalized_Weight * Vulnerability_Sectors, na.rm = TRUE),
#     weighted_sum_exposure = sum(Normalized_Weight * Exposure_Sectors_notnorm, na.rm = TRUE)
#   ) |>
#   ungroup()
#
# # Step 4: Normalize the weighted sums
# weighted_sums_norm <- weighted_sums |>
#   mutate(Weighted_sum_risk = normalize_min_max(weighted_sum_risk),
#          Weighted_sum_vulnerability = normalize_min_max(weighted_sum_vulnerability),
#          Weighted_sum_exposure = normalize_min_max(weighted_sum_exposure))
#
# # Step 5: Merge the regional data from R_r (containing regional risk, vulnerability, and exposure data)
# combined_risk_data <- weighted_sums_norm |>
#   left_join(R_r, by = "NUTS_NAME") |>
#   left_join(AR_r, by = "NUTS_NAME")
```

```
#
# # Check for NAs after joining
# combined_risk_data %>%
#   summarise_all(~ sum(is.na(.))) %>%
#   print()
#
# # Step 6: Calculate 'Risk_Region' using geometric mean with Response
# combined_risk_data <- combined_risk_data |>
#   mutate(Risk_Region = geometric_mean_with_response(Exposure_Regions, Vulnerability_Regions, Response))
#
# # Check if log function introduces NAs
# combined_risk_data <- combined_risk_data |>
#   mutate(log_response_check = log(1 + pmax(Response, 0.01)))
#
# # Step 7: Calculate Composite Risk, Vulnerability, and Exposure using the provided formula
# combined_risk_data <- combined_risk_data |>
#   mutate(
#     Composite_Risk = sqrt(Risk_Region * Weighted_sum_risk),
#     Composite_Vulnerability = sqrt(Vulnerability_Regions *
#                                    Weighted_sum_vulnerability),
#     Composite_Exposure = sqrt(Exposure_Regions * Weighted_sum_exposure)
#   )
#
# combined_risk_data <- combined_risk_data |>
#   mutate(
#     Composite_Risk = normalize_min_max_easy(Composite_Risk),
#     Composite_Vulnerability = normalize_min_max_easy(Composite_Vulnerability),
#     Composite_Exposure = normalize_min_max_easy(Composite_Exposure)
#   )
#
# # Check for NAs after calculations
# combined_risk_data %>%
#   summarise_all(~ sum(is.na(.))) %>%
#   print()
#
# # Select the final columns to display
# final_composite_results_ita <- combined_risk_data |>
#   left_join(sector_risk_with_weights_it, by = c("NUTS_NAME")) |>
#   select(Sector, NUTS_ID, NUTS_NAME, CNTR_CODE,
#          Composite_Risk, Composite_Vulnerability, Composite_Exposure,
#          Normalized_Weight, Total_Weight,
#          Weighted_sum_risk, Weighted_sum_vulnerability, Weighted_sum_exposure,
#          Risk_Region, Vulnerability_Regions, Exposure_Regions,
#          Risk_Sector, Vulnerability_Sectors, Exposure_Sectors)
#
# # Display the final composite results
# head(final_composite_results_ita)
#
# writexl::write_xlsx(final_composite_results_ita, "/Users/giocopp/Desktop/final_composite_results_ita.xlsx")

final_composite_results_ita <- readxl::read_xlsx("/Users/giocopp/Desktop/final_composite_results_ita.xlsx")
output_path <- file.path("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Manufactory Data/", "EU_Manufactory_Data.xlsx")
final_composite_results <- readxl::read_xlsx(output_path)

# Step 1: Get the NUTS2 shapefile for Europe from Eurostat
nuts2_map <- get_eurostat_geospatial(output_class = "sf", resolution = "10", nuts_level = 2, year = 2021)

# Step 2: Filter to include only EU27 countries based on CNTR_CODE
county_nuts2_map <- nuts2_map %>%
  filter(CNTR_CODE %in% c("IT"))

county_nuts2_map <- county_nuts2_map %>%
  left_join(final_composite_results_ita, by = "NUTS_ID")
```

Prepare plots:

```
### Risk

min <- min(county_nuts2_map$Composite_Risk, na.rm = TRUE)
median <- median(county_nuts2_map$Composite_Risk, na.rm = TRUE)
max <- max(county_nuts2_map$Composite_Risk, na.rm = TRUE)

Risk_map <- ggplot(county_nuts2_map) +
  geom_sf(aes(fill = Composite_Risk)) +
  scale_fill_viridis_c(
    option = "rocket",
    na.value = "white",
    direction = -1,
    begin = 0.2,
    end = 1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Risk Index"
  ) +
  theme_minimal() +
```

```
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )


### Exposure

min <- min(county_nuts2_map$Composite_Exposure, na.rm = TRUE)
median <- median(county_nuts2_map$Composite_Exposure, na.rm = TRUE)
max <- max(county_nuts2_map$Composite_Exposure, na.rm = TRUE)

Exposure_map <- ggplot(county_nuts2_map) +
  geom_sf(aes(fill = Composite_Exposure)) +
  scale_fill_viridis_c(
    option = "viridis",
    na.value = "white",
    direction = -1,
    begin = 0.2,
    end = 1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Exposure Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )


### Vulnerability

min <- min(county_nuts2_map$Composite_Vulnerability, na.rm = TRUE)
median <- median(county_nuts2_map$Composite_Vulnerability, na.rm = TRUE)
max <- max(county_nuts2_map$Composite_Vulnerability, na.rm = TRUE)

Vulnerability_map <- ggplot(county_nuts2_map) +
  geom_sf(aes(fill = Composite_Vulnerability)) +
  scale_fill_viridis_c(
    option = "mako",
    na.value = "white",
    direction = -1,
    begin = 0.2,
    end = 1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Vulnerability Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )
```

Save and print:

```
Risk_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Risk_map_MANUF_ITA.jpeg", Risk_map, width = 10, height = 7, dpi = 800)

Exposure_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Exposure_map_MANUF_ITA.jpeg", Exposure_map, width = 10, height = 7, dpi
= 800)

Vulnerability_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Vulnerability_map_MANUF_ITA.jpeg", Vulnerability_map, width = 10, height
= 7, dpi = 800)
```

Heatmap for Country Manufacturing

The primary objective of the heatmap is to visualize the risk levels associated with each manufacturing sector in each Italian region. This helps in identifying which sectors are at higher risk in specific regions.

By applying hierarchical clustering to both sectors and regions, the heatmap groups together sectors and regions with similar risk profiles. This clustering highlights patterns, similarities, and differences in risk across sectors and regions.

Prepare data:

```
library(cluster)

normalize_min_max_easy <- function(x) {
  min_value <- min(x, na.rm = TRUE)
  max_value <- max(x, na.rm = TRUE)
  norm_values <- (x - min_value) / (max_value - min_value)
}

country_final_composite_results <- final_composite_results %>%
  filter(CNTR_CODE %in% c("IT")) %>%
  select(c("NUTS_NAME", "Sector", "Sector_Region_Risk")) |>
  mutate(Sector_Region_Risk = normalize_min_max_easy(Sector_Region_Risk)) |>
  mutate(Sector_Region_Risk = round(Sector_Region_Risk * 100, 2))
```

Prepare plot:

```
# Prepare the data for clustering of Weighted Composite Risk
heatmap_data_weighted <- country_final_composite_results %>%
  spread(key = NUTS_NAME, value = Sector_Region_Risk) %>%
  column_to_rownames(var = "Sector") %>%
  as.matrix()

# Perform hierarchical clustering on rows and columns for Weighted Composite Risk
row_clusters_weighted <- hclust(dist(heatmap_data_weighted), method = "ward.D2") # Clustering sectors
col_clusters_weighted <- hclust(dist(t(heatmap_data_weighted)), method = "ward.D2") # Clustering regions

# Reorder the data based on clustering for Weighted Composite Risk
heatmap_data_weighted <- heatmap_data_weighted[row_clusters_weighted$order, col_clusters_weighted$order]

# Convert reordered matrix back to a long format for ggplot for Weighted Composite Risk
heatmap_long_weighted <- as.data.frame(as.table(heatmap_data_weighted)) %>%
  rename(Sector = Var1, Region = Var2, Sector_Region_Risk = Freq)

# Calculate the quartiles for Sector_Region_Risk
min <- min(country_final_composite_results$Sector_Region_Risk, na.rm = TRUE)
median <- median(country_final_composite_results$Sector_Region_Risk, na.rm = TRUE)
max <- max(country_final_composite_results$Sector_Region_Risk, na.rm = TRUE)

# Define the heatmap with quartiles and adjusted legend spacing
sector_region_heatmap <- ggplot(heatmap_long_weighted, aes(x = Region, y = Sector, fill = Sector_Region_Risk)) +
  geom_tile(color = "white") +
  # Adjust the color scale to show quartile values
  scale_fill_viridis_c(
    option = "rocket",
    direction = -1,
    name = "Sector-Region Risk",
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01)
  ) +
  labs(x = "Region", y = "Sector") +
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, size = 9),
    axis.text.y = element_text(size = 9),
    axis.title.x = element_text(size = 11, face = "bold"),
    axis.title.y = element_text(size = 11, face = "bold"),
    legend.position = "right",
```

```
    legend.title = element_text(size = 8, face = "bold"),
    legend.text = element_text(size = 7),
    legend.key.size = unit(0.6, "cm")
  ) +
  guides(
    fill = guide_colorbar(
      barwidth = 0.5,
      barheight = 7,
      ticks.colour = "black",
      ticks.linewidth = 0.5
    )
  )
```

Save and print:

```
print(sector_region_heatmap)


ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Heatmap_MANUF_ITA.jpeg", sector_region_heatmap, width = 10, height = 7,
dpi = 800)
```

Graph Showing the Highest Risk Regions for Each Sector and the Highest Risk Sector for Each Region

The graph shows, for each manufacturing sector in a country (e.g. Italy), the region where that sector faces the highest risk, with the risk calculation weighted by employment per sector per region. This means that sectors employing more people in a region have a greater impact on the region's overall risk profile. The graph highlights where high inherent sector risks align with significant employment, indicating regions where both economic and social impacts could be substantial.

A similar graph that shows, for each region, the sector where it faces the highest risk. This will help identify which sectors are most critical in terms of risk within each region.

Prepare data:

```
#
# ### Sector-wise
# # Filter the data for Italy and select necessary columns
# max_risk_per_sector <- country_final_composite_results %>%
#   group_by(Sector) %>%
#   filter(Sector_Region_Risk == max(Sector_Region_Risk, na.rm = TRUE)) %>%
#   ungroup()
#
# # In case of ties (multiple regions with the same max risk), select the first one
# max_risk_per_sector <- max_risk_per_sector %>%
#   distinct(Sector, .keep_all = TRUE)
#
#
# ### Region-wise
# # For each region, find the sector with the maximum risk
# max_risk_per_region <- final_composite_results_ita %>%
#   group_by(NUTS_NAME) %>%
#   filter(Sector_Region_Risk == max(Sector_Region_Risk, na.rm = TRUE)) %>%
#   ungroup()
#
# # In case of ties (multiple sectors with the same max risk), select the first one
# max_risk_per_region <- max_risk_per_region %>%
#   distinct(NUTS_NAME, .keep_all = TRUE)
```

Prepare plot:

```
# ### Highest Risk Region for each Manufacturing Sector
# # Create a bar chart
# sector_max_risk_plot <- ggplot(max_risk_per_sector, aes(x = reorder(Sector, Sector_Region_Risk), y = Sector_Region_Risk,
fill = Sector_Region_Risk)) +
#   geom_col(show.legend = FALSE) +
#   coord_flip() +  # Flip coordinates for better readability
#   scale_fill_viridis_c(option = "rocket", direction = -1, begin = 0.1, end = 1) +
#   geom_text(aes(label = NUTS_NAME), hjust = -0.1, size = 2.2) +  # Add region names as labels
#   labs(
#     x = "Sector",
#     y = "Sector-Region Risk"
#   ) +
#   theme_minimal() +
#   theme(
#     axis.text.y = element_text(size = 8),
#     axis.title.y = element_text(size = 10, face = "bold"),
#     axis.title.x = element_text(size = 10, face = "bold"),
#     plot.title = element_text(size = 12, face = "bold"),
#     plot.caption = element_text(size = 8)
#   )
#
```

```
# # Adjust y-axis limits if labels are cut off
# sector_max_risk_plot <- sector_max_risk_plot +
#   ylim(0, max(max_risk_per_sector$Sector_Region_Risk) * 1.35)
#
#
#
# ### Highest Risk Manufacturing Sector for each Region
# # Create a bar chart
# region_max_risk_plot <- ggplot(max_risk_per_region, aes(x = reorder(NUTS_NAME, Sector_Region_Risk), y = Sector_Region_Risk,
fill = Sector_Region_Risk)) +
#   geom_col(show.legend = FALSE) +
#   coord_flip() +  # Flip coordinates for better readability
#   scale_fill_viridis_c(option = "rocket", direction = -1, begin = 0.1, end = 1) +
#   geom_text(aes(label = Sector), hjust = -0.1, size = 2.2) +
#   labs(
#     x = "Region",
#     y = "Sector-Region Risk"
#   ) +
#   theme_minimal() +
#   theme(
#     axis.text.y = element_text(size = 8),
#     axis.title.y = element_text(size = 10, face = "bold"),
#     axis.title.x = element_text(size = 10, face = "bold"),
#     plot.title = element_text(size = 12, face = "bold"),
#     plot.caption = element_text(size = 8)
#   )
#
# # Adjust y-axis limits if labels are cut off
# region_max_risk_plot <- region_max_risk_plot +
#   ylim(0, max(max_risk_per_region$Sector_Region_Risk) * 1.35)
#
```

Save and print:

```
# # Display the plot
# sector_max_risk_plot
# region_max_risk_plot
#
# # Save the plot to a file
# ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Sector_Risk_MANUF_ITA.jpeg", sector_max_risk_plot, width = 10, height
= 7, dpi = 800)
#
# ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Region_Risk_MANUF_ITA.jpeg", sector_max_risk_plot, width = 10, height
= 7, dpi = 800)
```

EU Agriculture and Transportation Sector

Data preprocessing and normalization for exposure and vulnerabiltiy

Sectoral Risk

Sector Data: Manufacturing

Load data:

```
library(tidyverse)
library(FactoMineR)
library(dplyr)
library(readxl)
library(eurostat)
library(giscoR)

EU_agri <- read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Agri and Transp Data/EU_Agriculture_Data.xlsx")
EU_transp <- read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Agri and Transp Data/EU_Transportation_Data.xlsx")
EU_Region_Risk_Data <- read_xlsx("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Regional Data/Risk_Index_Region_Data.xlsx")
```

We skip normalization for sectoral data since there's no variation as we only have one sector and one EU aggregate value. Since there's no variation, the sectoral vulnerability and exposure indices will be constants.

Even if the sectoral risk is constant, it can still be useful as a baseline multiplier across sectors. This works if we think about different sectors (e.g., Agriculture vs. Transportation) having different inherent baseline risks due to global factors (e.g., Agriculture might be more exposed to decarbonisation globally compared to Transportation, even if both sectors face the same regional risks). The sectoral risk serves as a sector-specific baseline multiplier for how vulnerable or exposed each sector is in general. Region-specific differences are captured through R_r while the sectoral differences come from the constant across regions.

Eventual alternative:

Have a single risk index that combines both regional and sector-specific factors into a sectoral-regional specific risk:

Sectoral-Regional Risk: This would reflect how a particular sector (or subsector) is impacted by risks that are both inherent to the sector and specific to the region.

This approach would avoid the conceptual overlap we discussed earlier because the risk is treated holistically, without needing to split it into separate regional and sectoral components. However, such a sectoral-regional specific risk requires detailed data on how sector-specific risks vary geographically, which can be challenging to obtain.

Using Separate Regional and Sectoral Risks, the method is more valuable because:

- Increased Granularity: You capture more detailed sector-specific risks that can vary across subsectors, and these risks can differ significantly by region.
- More Accurate Weights: Weights based on subsectors give a more precise reflection of the sectoral composition of each region. For example, one region might have a high concentration of crop farming, while another might focus more on livestock, leading to different composite risks.

However, we are using separate regional and sectoral risks to be consistent with the method used in manufacturing.

```
EU_agri <- EU_agri |>
  mutate(GHG_EMISS = GHG_EMISS/NORM_noffarms,
         ENERG_fossil = ENERG_fossil/ENERG_final_cons,
         ENERG_RE= ENERG_RE/ENERG_final_cons,
         ENERG_final_cons_perfarm = ENERG_final_cons/NORM_noffarms,
         LAB_nfarmers_perfarm = LAB_nfarmers/NORM_noffarms,
         SUPCH_exp_share = SUPCH_exp_share/NORM_noffarms,
         SUPCH_exp_euros = SUPCH_exp_euros/NORM_noffarms,
         SUPCH_imp_share = SUPCH_imp_share/NORM_noffarms,
         SUPCH_imp_euros = SUPCH_imp_euros/NORM_noffarms,
         TECH_BERD = TECH_BERD/NORM_noffarms,
         FIN_AGRI = FIN_AGRI/NORM_noffarms
         )

EU_transp <- EU_transp |>
  mutate(GHG_EMISS = GHG_EMISS/NORM_nofenterpr,
         ENERG_fossil = ENERG_fossil/ENERG_final_cons,
         ENERG_RE= ENERG_RE/ENERG_final_cons,
         ENERG_final_cons_perenterpr = ENERG_final_cons/NORM_nofenterpr,
         SUPCH_exp_share = SUPCH_exp_share/NORM_nofenterpr,
         SUPCH_exp_euros = SUPCH_exp_euros/NORM_nofenterpr,
         SUPCH_imp_share = SUPCH_imp_share/NORM_nofenterpr,
         SUPCH_imp_euros = SUPCH_imp_euros/NORM_nofenterpr,
         TECH_BERD = TECH_BERD/NORM_nofenterpr,
         FIN_TRANSP = FIN_TRANSP/NORM_nofenterpr)
```

```
# Define the function to calculate vulnerability and risk and return a dataset
calculate_vuln_and_risk <- function(data, exposure_var, cols_to_remove, vuln_columns) {
  exposure <- data[[exposure_var]]

  vuln <- data %>%
    select(-all_of(cols_to_remove)) %>%
    mutate(total_sum = rowSums(across(everything()))) %>%
    mutate(vuln = total_sum - rowSums(across(all_of(vuln_columns)))) %>%
    pull(vuln)

  risk <- sqrt(vuln * exposure)

  # Return a dataset with exposure, vulnerability, and risk
  result <- data.frame(
    Sector = data$Sector,
    Exposure = exposure,
    Vulnerability = vuln,
    Risk = risk
  )

  return(result)
}

# Use the function for Agriculture
R_s_agri <- calculate_vuln_and_risk(
  data = EU_agri,
  exposure_var = "GHG_EMISS",
  cols_to_remove = c("Sector", "ENERG_final_cons", "GHG_EMISS", "NORM_noffarms"),
  vuln_columns = c("ENERG_RE", "LAB_nfarmers", "TECH_BERD", "FIN_AGRI")
)

# Use the function for Transportation
R_s_transp <- calculate_vuln_and_risk(
  data = EU_transp,
  exposure_var = "GHG_EMISS",
  cols_to_remove = c("Sector", "ENERG_final_cons", "GHG_EMISS", "NORM_nofenterpr"),
  vuln_columns = c("ENERG_RE", "LAB_npempl", "TECH_BERD", "FIN_TRANSP")
)

agri_weights <- read_excel("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Agri and Transp Data/WEIGHTS_agriempl.xlsx", sheet =
"Sheet 1")
transp_weights <- read_excel("/Users/giocopp/Desktop/LOCALISED 7.1/DATA/EU Agri and Transp Data/WEIGHTS_transpemp.xlsx")

agri_weights <- agri_weights %>%
  filter(NUTS_ID %in% EU_Region_Risk_Data$NUTS_ID)

transp_weights <- transp_weights %>%
  filter(NUTS_ID %in% EU_Region_Risk_Data$NUTS_ID)

# setdiff(EU_Region_Risk_Data$NUTS_ID, transp_weights$NUTS_ID)

agri_weights <- agri_weights %>%
  mutate(across(everything(), ~ na_if(., ":"))) |>
  mutate(AWU = as.numeric(na_if(AWU, ":")))

# Extract the country code from the first two characters of NUTS_ID
agri_weights <- agri_weights %>%
  mutate(CNTR_CODE = substr(NUTS_ID, 1, 2))

transp_weights <- transp_weights %>%
  mutate(CNTR_CODE = substr(NUTS_ID, 1, 2))

# Impute NA values using the average of the country
agri_weights <- agri_weights %>%
  group_by(CNTR_CODE) %>%
  mutate(across(where(is.numeric), ~ ifelse(is.na(.), mean(., na.rm = TRUE), .))) %>%
  ungroup()

agri_weights <- agri_weights %>%
  mutate(total_employment = sum(AWU),
         weight = AWU / total_employment)

transp_weights <- transp_weights %>%
  mutate(total_employment = sum(transp_empl),
         weight = transp_empl / total_employment)

options(scipen = 999)

normalize_min_max_easy <- function(x) {
  min_value <- min(x, na.rm = TRUE)
  max_value <- max(x, na.rm = TRUE)
  norm_values <- (x - min_value) / (max_value - min_value)
}

# Get regional risk
```

```r
R_r <- EU_Region_Risk_Data |>
  select(NUTS_ID, CNTR_CODE, NUTS_NAME, Risk_Region, Vulnerability_Regions, Exposure_Regions)

# For Agriculture
composite_agri <- R_r |>
  left_join(agri_weights, by = "NUTS_ID") |>
  mutate(
    # Composite Exposure calculation
    Composite_Exposure = weight * sqrt(Exposure_Regions * R_s_agri$Exposure),
    Composite_Exposure = round(normalize_min_max_easy(Composite_Exposure) * 100, 2),

    # Composite Vulnerability calculation
    Composite_Vulnerability = weight * sqrt(Vulnerability_Regions * R_s_agri$Vulnerability),
    Composite_Vulnerability = round(normalize_min_max_easy(Composite_Vulnerability) * 100, 2),

    # Composite Risk calculation
    Composite_Risk = weight * sqrt(Risk_Region * R_s_agri$Risk),
    Composite_Risk = round(normalize_min_max_easy(Composite_Risk) * 100, 2)
  )

# For Transportation
composite_transp <- R_r |>
  left_join(transp_weights, by = "NUTS_ID") |>
  mutate(
    # Composite Exposure calculation
    Composite_Exposure = weight * sqrt(Exposure_Regions * R_s_transp$Exposure),
    Composite_Exposure = round(normalize_min_max_easy(Composite_Exposure) * 100, 2),

    # Composite Vulnerability calculation
    Composite_Vulnerability = weight * sqrt(Vulnerability_Regions * R_s_transp$Vulnerability),
    Composite_Vulnerability = round(normalize_min_max_easy(Composite_Vulnerability) * 100, 2),

    # Composite Risk calculation
    Composite_Risk = weight * sqrt(Risk_Region * R_s_transp$Risk),
    Composite_Risk = round(normalize_min_max_easy(Composite_Risk) * 100, 2)
  )


composite_transp |>
  filter(CNTR_CODE.x == "IT")

# A tibble: 21 × 14
   NUTS_ID CNTR_CODE.x NUTS_NAME.x            Risk_Region Vulnerability_Regions
   <chr>   <chr>       <chr>                        <dbl>                 <dbl>
 1 ITC1    IT          Piemonte                     0.196                 0.319
 2 ITC2    IT          Valle d'Aosta/Vallée d…      0.263                 0.636
 3 ITC3    IT          Liguria                      0.236                 0.562
 4 ITC4    IT          Lombardia                    0.122                 0.232
 5 ITF1    IT          Abruzzo                      0.297                 0.609
 6 ITF2    IT          Molise                       0.438                 0.675
 7 ITF3    IT          Campania                     0.255                 0.603
 8 ITF4    IT          Puglia                       0.356                 0.597
 9 ITF5    IT          Basilicata                   0.385                 0.634
10 ITF6    IT          Calabria                     0.378                 0.658
# ℹ 11 more rows
# ℹ 9 more variables: Exposure_Regions <dbl>, NUTS_NAME.y <chr>,
#   transp_empl <dbl>, CNTR_CODE.y <chr>, total_employment <dbl>, weight <dbl>,
#   Composite_Exposure <dbl>, Composite_Vulnerability <dbl>,
#   Composite_Risk <dbl>
```

Visualization

Agriculture

```r
# Load necessary libraries
library(sf)
library(dplyr)
library(ggplot2)
library(readxl)
library(eurostat)
library(tidyverse)

# Step 1: Get the NUTS2 shapefile for Europe from Eurostat
nuts2_map <- get_eurostat_geospatial(output_class = "sf", resolution = "10", nuts_level = 2, year = 2021)

# Step 2: Filter to include only EU27 countries based on CNTR_CODE
eu_nuts2_map <- nuts2_map %>%
  filter(CNTR_CODE %in% c("AT", "BE", "BG", "HR", "CY", "CZ", "DK", "EE", "FI", "FR", "DE",
                          "EL", "HU", "IE", "IT", "LV", "LT", "LU", "MT", "NL", "PL",
                          "PT", "RO", "SK", "SI", "ES", "SE"))

# Step 3: Filter out non-continental regions (like islands)
# Use the bounding box to exclude regions with low latitude (e.g., Canary Islands)
# You can adjust the latitude and longitude cutoffs as needed
```

```
nuts2_map <- nuts2_map %>%
  mutate(NUTS_ID = as.character(NUTS_ID))

continental_eu_nuts2_map <- nuts2_map %>%
  filter(!grepl("ES7", NUTS_ID),
         !grepl("FRY", NUTS_ID),
         !grepl("PT2", NUTS_ID),
         !grepl("TR", NUTS_ID))

map_data <- continental_eu_nuts2_map %>%
  left_join(composite_agri, by = "NUTS_ID")

# Load required libraries
library(ggplot2)
library(dplyr)
library(sf)
library(RColorBrewer)
library(viridis)
library(cowplot)


### Risk

min <- min(map_data$Composite_Risk, na.rm = TRUE)
median <- median(map_data$Composite_Risk, na.rm = TRUE)
max <- max(map_data$Composite_Risk, na.rm = TRUE)

Risk_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Risk)) +
  scale_fill_viridis_c(
    option = "rocket",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Risk Index"  # Add legend title
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )

Risk_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Risk_map_AGRI_EU.jpeg", Risk_map, width = 10, height = 7, dpi = 800)
```

```
### Exposure

min <- min(map_data$Composite_Exposure, na.rm = TRUE)
median <- median(map_data$Composite_Exposure, na.rm = TRUE)
max <- max(map_data$Composite_Exposure, na.rm = TRUE)

Exposure_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Exposure)) +
  scale_fill_viridis_c(
    option = "viridis",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Exposure Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
```

```
    panel.spacing = unit(0.8, "lines")
  )


Exposure_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Exposure_map_AGRI_EU.jpeg", Exposure_map, width = 10, height = 7, dpi = 800)
```

```
### Vulnerability

min <- min(map_data$Composite_Vulnerability, na.rm = TRUE)
median <- median(map_data$Composite_Vulnerability, na.rm = TRUE)
max <- max(map_data$Composite_Vulnerability, na.rm = TRUE)

Vulnerability_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Vulnerability)) +
  scale_fill_viridis_c(
    option = "mako",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Vulnerability Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )

Vulnerability_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Vulnerability_map_AGRI_EU.jpeg", Vulnerability_map, width = 10, height = 7, dpi = 800)
```

Transportation

```
# Load necessary libraries
library(sf)
library(dplyr)
library(ggplot2)
library(readxl)
library(eurostat)
library(tidyverse)

# Step 1: Get the NUTS2 shapefile for Europe from Eurostat
nuts2_map <- get_eurostat_geospatial(output_class = "sf", resolution = "10", nuts_level = 2, year = 2021)

# Step 2: Filter to include only EU27 countries based on CNTR_CODE
eu_nuts2_map <- nuts2_map %>%
  filter(CNTR_CODE %in% c("AT", "BE", "BG", "HR", "CY", "CZ", "DK", "EE", "FI", "FR", "DE",
                          "EL", "HU", "IE", "IT", "LV", "LT", "LU", "MT", "NL", "PL",
                          "PT", "RO", "SK", "SI", "ES", "SE"))

# Step 3: Filter out non-continental regions (like islands)
# Use the bounding box to exclude regions with low latitude (e.g., Canary Islands)
# You can adjust the latitude and longitude cutoffs as needed
continental_eu_nuts2_map <- nuts2_map %>%
  filter(!grepl("ES7", NUTS_ID),
         !grepl("FRY", NUTS_ID),
         !grepl("PT2", NUTS_ID),
         !grepl("TR", NUTS_ID))

map_data <- continental_eu_nuts2_map %>%
  left_join(composite_transp, by = "NUTS_ID")

### Risk

min <- min(map_data$Composite_Risk, na.rm = TRUE)
median <- median(map_data$Composite_Risk, na.rm = TRUE)
```

```r
max <- max(map_data$Composite_Risk, na.rm = TRUE)

Risk_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Risk)) +
  scale_fill_viridis_c(
    option = "rocket",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Risk Index"  # Add legend title
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )

Risk_map
```

```r
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Risk_map_TRANSP_EU.jpeg", Risk_map, width = 10, height = 7, dpi = 800)
```

```r
### Exposure

min <- min(map_data$Composite_Exposure, na.rm = TRUE)
median <- median(map_data$Composite_Exposure, na.rm = TRUE)
max <- max(map_data$Composite_Exposure, na.rm = TRUE)

Exposure_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Exposure)) +
  scale_fill_viridis_c(
    option = "viridis",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
    labels = scales::number_format(accuracy = 0.01),
    name = "Exposure Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )


Exposure_map
```

```r
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Exposure_map_TRANSP_EU.jpeg", Exposure_map, width = 10, height = 7, dpi
= 800)
```

```r
### Vulnerability

min <- min(map_data$Composite_Vulnerability, na.rm = TRUE)
median <- median(map_data$Composite_Vulnerability, na.rm = TRUE)
max <- max(map_data$Composite_Vulnerability, na.rm = TRUE)

Vulnerability_map <- ggplot(map_data) +
  geom_sf(aes(fill = Composite_Vulnerability)) +
  scale_fill_viridis_c(
    option = "mako",
    na.value = "white",
    direction = -1,
    breaks = c(min, median, max),
```

```
    labels = scales::number_format(accuracy = 0.01),
    name = "Vulnerability Index"
  ) +
  theme_minimal() +
  theme(
    axis.text = element_blank(),
    axis.ticks = element_blank(),
    panel.grid = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 11),
    strip.text = element_text(size = 9, face = "bold"),
    legend.title = element_text(size = 9, face = "bold"),
    legend.text = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    legend.position = "right",
    panel.spacing = unit(0.8, "lines")
  )

Vulnerability_map
```

```
ggsave("/Users/giocopp/Desktop/LOCALISED 7.1/FIGURES/Vulnerability_map_TRANSP_EU.jpeg", Vulnerability_map, width = 10, height
= 7, dpi = 800)
```