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CrossEU

D1.3 - Data on the sectoral impacts of selected mitigation and adaptation strategies at European level. Interim Report

WP1 - Task 1.3

June 2025

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Executive Summary

The CROSSEU project aims to advance climate resilience by supporting informed decision-making to mitigate against or adapt to climate change. In Work Package 1 (WP1) of the CROSSEU project we focus on developing a framework for assessing climate-related bio-geo-physical and socio-economic risks. The main goal of the deliverable D1.3 (due Month 30) is to analyse the distributional consequences of extreme weather events to assess regional vulnerabilities at local level over Europe and inform on social and economic equity of mitigation and adaptation strategies. Moreover, it extends the global economic ENGAGE model to represent agricultural production, consumption and trade at the NUTS-2 level to assess socioeconomic impacts, risks and opportunities.
This interim deliverable (due Month 18) presents the methodologies that have been developed in task T1.3 of WP1 to evaluate the socioeconomic risks of climate change in Europe and analyse the equity implications of mitigation and adaptation policies. After a systematic literature review on how climate change affects income, gender, regional inequalities, and agricultural systems, the development of the modelling framework is presented. Two complementary methodologies are applied in this framework: an Empirical Econometric modelling and a Global Computable General Equilibrium (CGE) model. The econometric component aims to estimate the distributional impacts of climate and macroeconomic variables on income inequality, while the CGE model simulates the propagation of climate-induced shocks across sectors and regions over Europe, focusing on the agricultural sector. Together, these two approaches enhance the analytical capacity in WP1 to assess the socioeconomic impacts of climate change and adaptation strategies to cope with it.

As this is an interim report, please note that the full results of the socioeconomic assessment, conducted using the models presented in this interim report, will be made available in the final deliverable.

Keywords

Adaptation, Climate Change, Computable General Equilibrium (CGE), Distributional Effects, Econometric Modelling, Extreme Weather Events, Heat Stress, Income Distribution, Income Inequality, Poverty, Labour Productivity, Socioeconomic Impacts, Vulnerability

Abbreviations and acronyms

Acronym	Description
AEZ	Agro-Ecological Zone
CAP	Common Agricultural Policy
CES	Constant Elasticity of Substitution
CGE	Computable General Equilibrium
CID	Climate Impact Driver
CPI	Consumer Price Index
CR	Climate Risk
DCPS	Domestic Credit to the Private Sector
DLNM	Distributed Lag Non-linear Model
EANO	Economic Analyses of Negotiated Outcome
ECF	Excess Cold Factor
EHF	Excess Heat Factor
ERA5	Fifth Generation ECMWF Atmospheric Reanalysis of the Global Climate
EEA	European Environment Agency
EU15 / EU13	EU Member States before/after 2004 enlargement
FIGARO	Full International and Global Accounts for Research in Input-Output Analysis
FLFP	Female Labour Force Participation
GAEZ	Global Agro-Ecological Zones
GCM	General Circulation Model
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation

GTAP	Global Trade Analysis Project
Gini_index	Gini Coefficient of Household Disposable Income
HW_IF	Heatwave Intensity-Frequency Interaction Index
IAM	Integrated Assessment Model
ILO	International Labour Organization
IPCC	Intergovernmental Panel on Climate Change
IQ_PC	Institutional Quality Principal Component
ISCED	International Standard Classification of Education
LIS	Luxembourg Income Study
LMIC	Low- and Middle-Income Country
LUISA	Land Use-based Integrated Sustainability Assessment
METEOCAT	Servei Meteorològic de Catalunya
MR-SAM	Multi-Regional Social Accounting Matrix
NACE	NACE
NF13	Normalised Frequency Index (13-month rolling average)
NUTS-2	Nomenclature of Territorial Units for Statistics Level 2
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PC_ln_GDP	Principal Component of Sectoral GDP
PIP	Poverty and Inequality Platform (World Bank)
RAS	RAS balancing algorithm (bi-proportional matrix balancing)
R10mm_IF	Rainfall >10mm Intensity-Frequency Interaction Index
RCP	Representative Concentration Pathway
RMSE	Root Mean Squared Error

SAM	Social Accounting Matrix
SSP	Shared Socioeconomic Pathway
SUT	Supply and Use Table
SWIID	Standardised World Income Inequality Database
tmean, tmin, tmax	Daily Mean, Minimum, and Maximum Temperature
UNEMP_rate	Unemployment Rate
WBGT	Wet-Bulb Globe Temperature
WDI	World Development Indicators
WEMC	World Energy & Meteorology Council
WGI	World Governance Indicators

1. Introduction

Climate change presents a profound and escalating challenge to both natural systems and human societies, with wide-ranging environmental, economic, and social consequences. Its environmental manifestations are extensive and multifaceted, including intensified hydrological cycles, rising global temperatures, changes in the statistics of extreme events, sea-level rise, melting ice, and ocean acidification. These changes disrupt natural ecosystems, threaten biodiversity, and contribute to the increasing frequency and severity of natural disasters such as floods, droughts, hurricanes, erosion, and heatwaves.

These environmental disruptions carry significant socio-economic consequences that reverberate across sectors and regions. For instance, labour productivity declines as high temperatures increase work interruptions, slow work pace, and raise injury risks, reducing safe working hours—especially in outdoor, labour-intensive settings (Ebi et al., 2021; ILO, 2019; Kjellstrom et al., 2016). Simultaneously, heat stress impairs crop yields by disrupting essential processes such as photosynthesis, development, leading to reduced growth and productivity. (Blanco et al., 2017; Hasegawa et al., 2022; Wing et al., 2021). These combined pressures threaten both human and agricultural performance, amplifying economic vulnerability.

Beyond labour impacts, climate change exacerbates existing social and economic inequalities, with vulnerability varying significantly across regions and countries and affects, particularly, developing nations. It poses a greater threat to exposed and resource-constrained communities—particularly low-income groups, indigenous peoples, and other disadvantaged groups—who often lack the capacity to adapt effectively. As Tol et al. (2004) argue, while poverty is a key contributor to climate vulnerability (and vice-versa), it is not synonymous with it. Understanding vulnerability requires considering a broader set of factors beyond economic status, including the dynamic and context-specific nature of susceptibility across different communities.

These vulnerabilities are further magnified by the intricate interdependence of global supply chains. Given the increasing integration of agricultural production, trade, and consumption across borders, climate-induced disruptions in one region can rapidly cascade through international systems. For example, extreme weather events affecting crop yields in a major exporting country can reduce global food availability, destabilize trade flows, and heighten market volatility—ultimately threatening food security and socio-economic stability worldwide (Khalfaoui et al., 2024; Sun et al., 2024; Wenz & Levermann, 2016). Historical events underscore this fragility: the 2007–2008 food price crisis, triggered by climate anomalies and poor harvests in key regions like Australia and parts of Asia, led to sharp price spikes and food riots in over 30 countries (Bellemare, 2015; UNCTAS, 2008; Wiggins & Levy, 2008). Similarly, the 2010 droughts in Russia, Ukraine, and Kazakhstan prompted wheat export bans, amplifying global prices and severely impactingimport-dependent regions such as North Africa and South Asia (Hunt et al., 2021; Welton, 2011).

These complex and interconnected dynamics underscore the need for robust analytical tools to assess how climate-induced shocks propagate through economic systems. Computable General Equilibrium (CGE) models are economy-wide models that simulate the interactions between different sectors, households, and governments, capturing economy-wide interactions on economic shocks and policy interventions. CGE models have become essential tools in this regard, offering a comprehensive framework to assess how climate change affects agricultural production, trade, and welfare on a global scale. They are particularly suited for analysing climate change impacts on agriculture because they capture inter-sectoral linkages—such as agriculture's dependence on other sectors (industry, transportation), its role in food supply, and its cascading effects across industries through supply chains. Furthermore, CGE models account for general equilibrium effects, including changes in prices, resource allocation, income distribution, and trade flows, which partial equilibrium models might overlook. Importantly, they also enable the analysis of adaptation and mitigation strategies within an economy-wide framework (Britz & Witzke, 2014; Calzadilla et al., 2013; Hertel, 1997; Palatnik & Roson, 2012; Valin et al., 2014).

To further enhance the analytical power of CGE models in assessing climate impacts, recent methodological innovations have focused on integrating detailed income distribution modelling with macroeconomic and climate variables. One such approach involves estimating income distributions at the percentile level using panel regression techniques that incorporate sectoral GDP, institutional quality (encompassing legal systems, political structures, and economic frameworks), labour market dynamics, and climate extremes. This allows for a more granular understanding of how climate shocks affect different segments of the population, particularly the most vulnerable.

By embedding these empirically derived income distributions into CGE frameworks, policy modellers can simulate not only aggregate macroeconomic outcomes but also the distributional implications of climate change—capturing shifts in poverty incidence, income inequality, and polarisation across the income spectrum. This integration enables a more comprehensive assessment of how climate-induced shocks interact with structural economic characteristics, institutional quality, and sectoral dynamics, thereby enriching the policy relevance of CGE-based scenario analysis.

Crucially, this modelling approach accounts for the heterogeneity of climate impacts across income groups and economic sectors, reflecting the asymmetric exposure and adaptive capacity observed in real-world settings. It also facilitates the ex-ante evaluation of targeted policy responses—such as redistributive transfers, labour market interventions, or sector-specific adaptation strategies—within a consistent, economy-wide equilibrium framework. As such, this integrated methodology represents a significant advancement in climate-economy modelling, bridging the gap between macro-level simulation and micro-level distributional analysis, and enhancing the capacity of CGE models to inform equitable and resilient policy design.

1.1. Purpose of this interim deliverable

The final deliverable D1.3 is scheduled for submission in Month 30 of the CROSSEU project (June 2026), in alignment with the agreement reached with the Project Officer. This report serves as an "interim deliverable" of D1.3, providing the advancements of the work achieved to date in task T1.3 of WP1 of the CROSSEU project. During the first 18 months of the project, literature reviews and the development of methods and models have been undertaken. The outputs of the socioeconomic modelling currently in development will be presented in the finalised deliverable, schedule for submission in Month 30.

This interim deliverable describes the initial work of the socioeconomic modelling framework developed under Task T1.3 to assess the distributional impacts of climate change. It outlines the dual-modelling approach that integrates climate and socioeconomic data through two complementary frameworks: an econometric model and a global CGE (subnational-ENGAGE) model. The econometric component provides the empirical foundation, using panel regression models to estimate the relationship between macroeconomic and climate variables and income distributions across percentiles. These estimates inform and calibrate the CGE simulations, specifically through the integration of a poverty module, which enables the model to capture distributional effects more accurately. The CGE framework offers a structural representation of how climate shocks propagate through the economy—both domestically and across borders via trade linkages—affecting sectoral outputs, factor returns, and ultimately, income distribution. The main objective of the CGE model is to assess the economy-wide impacts of climate change and adaptation strategies in the agricultural sector, taking into account projected changes in crop yields and labour productivity due to climate change.

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1.2. Structure of the deliverable

The remainder of this deliverable is structured as follows:

- Section 2: Summarises findings from 78 studies on how climate change exacerbates income, gender, and regional inequalities, with a focus on Europe.
- Section 3: Reviews key CGE models and methods used to simulate climate impacts on agriculture and economic systems.
- Section 4: Identifies limitations in current models.
- Section 5: Presents the combined econometric and CGE framework developed to assess climate-induced socioeconomic impacts across European NUTS-2 regions.
- Section 6: Details the datasets used for modelling, including income, climate, economic, and trade data.
- Section 7: Explains the statistical and modelling techniques used to estimate income distributions and simulate climate risks.
- Section 8: Conclusions summarizing key insights

2. Empirical Evidence on Socioeconomic Risks of Climate Change

2.1. Systematic Review Methodology

To establish a robust evidence base on the socioeconomic risks of climate change in Europe, this study conducted a structured review of 78 peer-reviewed articles. The study reviews the socioeconomic impacts of climate change on existing inequalities from the current literature. Following the systematic literature methodology by Tranfield et al. (2003), the study starts by defining the objective of the study before proceeding to answer the "what," "how," and "why" questions. Queries were conducted in the Web of Science and Scopus databases in May 2024. Various keywords which were connected by Boolean operators constituted the search queries, filtering for journal articles on climate change and extreme weather event impacts. Books, book chapters and working papers were excluded from the results and not included in the final discussion of this study.

Though the primary focus of this review paper was Europe, worldwide literatures were required to give initial context and provide general background on the impacts of climate change and extreme weather events. For Europe-restricted studies, apart from a broad search on the socioeconomic risks of climate change, the search query was separated into various aspects of inequalities identified from the broader search. The Boolean operator "AND" connected the climate change or extreme weather events impacts with socioeconomic risks or inequalities. A list of the keywords used in the study is provided in Figure 1.

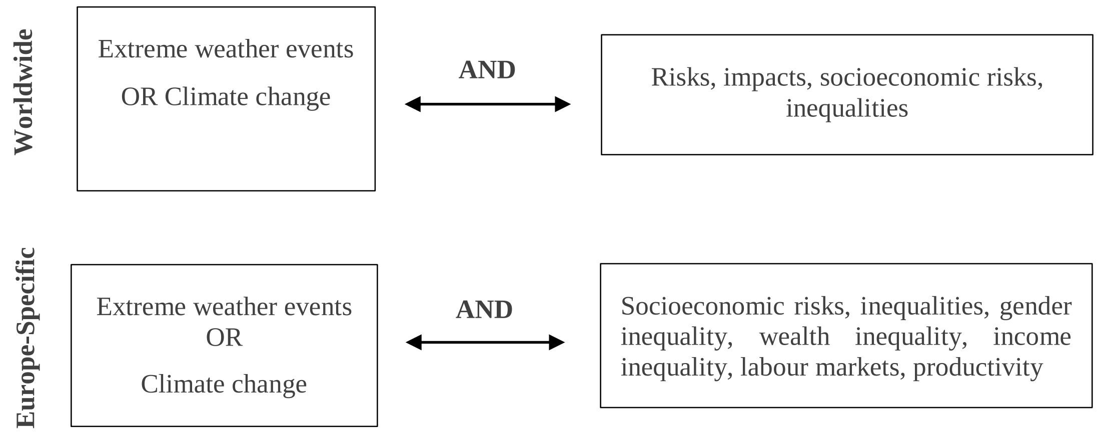

Figure 1: Schematic representation of query keywords

This large sample was due to the broad ambiguity of some words which led to the inclusion of some irrelevant studies. After reading titles, abstracts, and full text of the search result only 24 studies were found to be directly related to the scope of the study, of which 9 were duplicates. The criteria for inclusion were: (1) articles focused on "Climate Change/extreme weather events and socioeconomic risks", (2) specific to Europe or includes Europe and (3) studies with empirical analysis on how climate change exacerbates existing inequalities.

Furthermore, to search for other relevant studies, the citation log of the selected studies was examined using the Google Scholar search engine and 12 more studies were added.

Finally, studies that discuss extreme weather events or the effects of climate change more broadly have also been included in the literature review. Altogether, including these studies that provide a general context on the research area, a total of 78 studies constitutes the sample for this review.

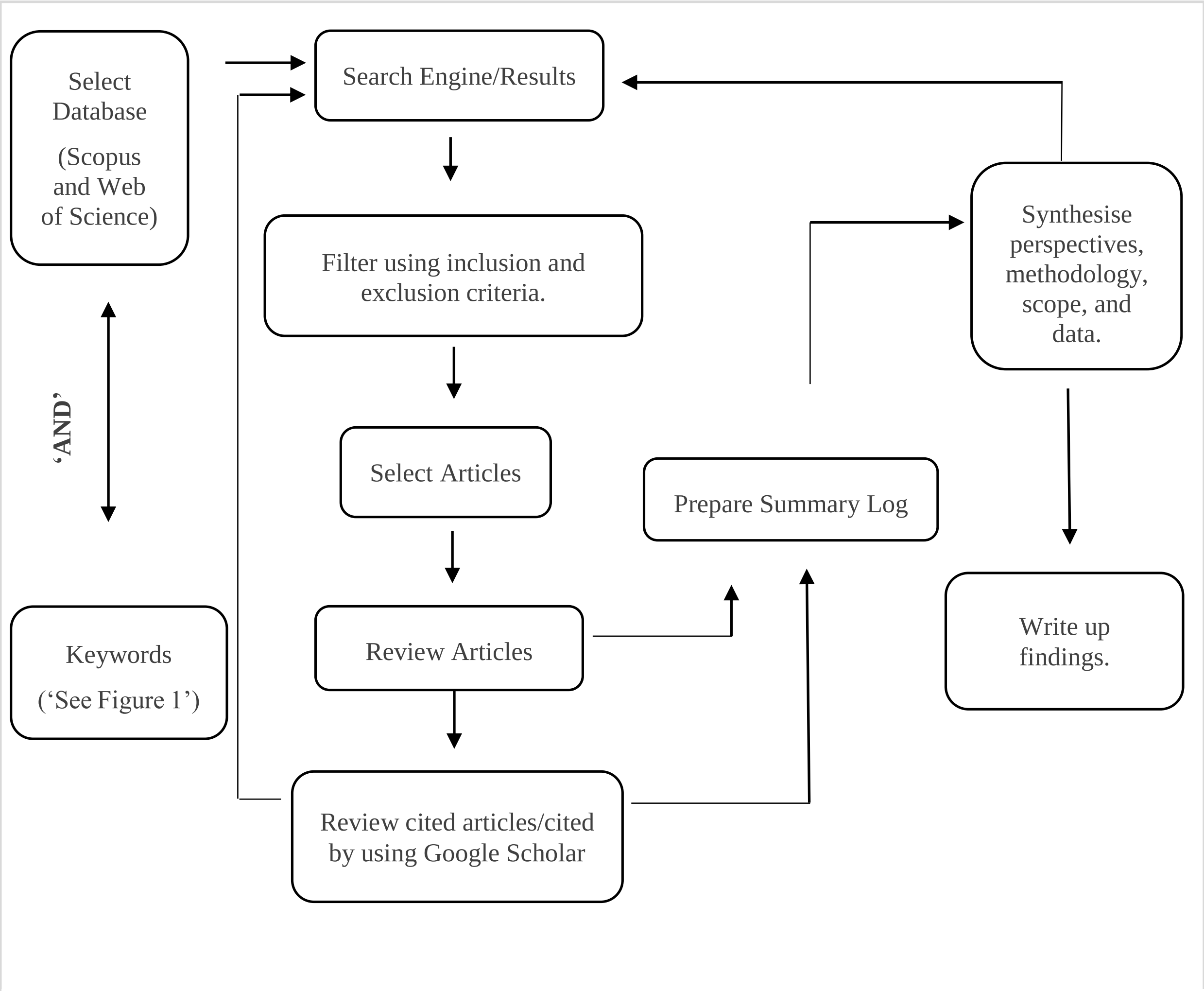

Figure 2: Illustration of the review process applied in this study

As depicted in Error! Reference source not found., there was constant feedback to the literature, ensuring that selected publications were thoroughly examined and analysed to synthesise perspectives, methodologies, scope, sources, and datasets. To aid in this activity, a summary log document was created on Microsoft excel to clearly highlight the features of all selected papers.

In this section, a general overview of the subject is discussed in 2.2, preliminary information on the reviewed literature is presented in 2.3, details on panel studies with Europe inclusive are contained in section 2.4 and studies specific to Europe are covered in Section 2.5. Section 2.7 and 2.8 focus on methods of estimation, data employed, scope and findings.

2.2. General overview on climate change, extreme weather events and inequalities at global level

The literature broadly acknowledges that climate change exacerbates existing economic inequalities, with poorer countries more exposed to the negative effects of climate change than wealthier countries. Poorer countries lack the resources to protect themselves against the negative consequences of climate change, and they are typically located in warmer locations where further warming could be harmful to health and production (Berlemann & Wenzel, 2018). Countries also suffer the adverse impacts of climate change based on their geographical location.

According to Diffenbaugh & Burke (2019) lower latitudes countries are more vulnerable to the effects of climate change than higher latitude countries. Kellenberg & Mobarak (2008) identified non-linearities between stages of economic development and natural disaster induced fatalities. They noted that for disasters such as floods, windstorms, and landslides, where the risk is influenced by human behaviour, mortality tends to rise with increasing income, during the transition from low- to middle-income countries (LMIC), before eventually declining when achieving high-income status.

Mortality rates are higher in the early phases of development because countries often lack sufficient investments in preventive measures to protect life. As economic development advances, these measures become more affordable and accessible, reducing the risk of death related to climate change extreme events. Inequalities arising from climate change and extreme weather events across segments of a population within a country also exist. Belasen & Polachek (2009) referred to hurricanes in the United States as exogenous shocks to economic performance which affects wages and size of the labour force. In areas directly affected by natural disasters, employment drops while earnings rise, indicating a negative labour supply impact but altered labour demand in specific sectors. Also, neighbouring regions experience an influx of workers, leading to stable employment but reduced earnings due to a positive labour supply shock. Bui et al. (2014) stated that natural disasters have significantly aggravated poverty and increased income inequality among households in Vietnam. Emphasising the long-lasting effects of extreme weather events, Lynham et al. (2017) reported that even after many years of Hawaii's devasting tsunami, unemployment in the affected city remains 32% higher and population was still 9% lower than it would have been if the tsunami had not occurred. Similar studies on the within country impacts of climate change exist for other countries such as Ethiopia (Thiede, 2014), Mexico (Sakai et al., 2017), and India (Sedova et al., 2019).

Empirical studies have also examined the relationship between climate change and income inequality. Jorgenson et al. (2015) reported a positive relationship between carbon emissions and income inequality in the United States. Huynh & Hoang (2024) stated that rising temperature and precipitation levels exacerbates income inequality in several Asian countries. Issoufou-Ahmed & Sebri (2024) attributed income inequality in sub-Saharan Africa to climate change vulnerability and Ashenafi (2022) concluded that the greenhouse gas emissions widen income inequality in Africa. Mideksa (2010) projected that climate shock reduces output in the sector with the strongest forward and backward linkage to the rest of the economy and redistributes income by changing the returns to inputs owned by various agents, raising income inequality. Baarsch et al. (2020a) and Alam et al. (2017) evidenced similar impacts of climate change on income inequality in African countries and Malaysia. When a country experiences recurrent disasters, the cumulative socioeconomic effects of many extreme weather occurrences exacerbate income disparity.

Another perception on the effects of climate change on income inequality also exists. Chisadza et al. (2023) noted that climate change negatively impacts sustainable development in the United States though increases in income inequality Some short-term effects such as a rise in inequality due to increasing temperatures may be temporary and tend to reverse as temperature related anomalies normalise.

Similarly, by determining the income groups most affected by natural disasters, Pleninger (2022) suggested that because middle income earners are primarily affected by natural disasters, income inequality levels remain unchanged. Otrachshenko & Popova (2022) noted that while extreme temperatures and precipitation affect Russia's GDP per capita, it has no effect on income inequality. They noted that although poorer regions may suffer due to reallocation of labour, price increases and changes in employment structure, the effects of extremely cold days or extreme precipitation levels have limited impact on the country's economic activity and income levels.

Although economic and socioeconomic criteria usually define gender equality, the literature also highlights the harmful effects of extreme weather events on gender equality (Terry, 2009). For example, climate change can worsen gender disparities by impacting women's health, education, and economic opportunities. In LMIC, women already suffer from reduced mobility to the non-agricultural sector and have limited access to information which increases their vulnerability to extreme weather events (Roy Chowdhury et al., 2021; Shamsuddoha et al., 2024). Extreme weather events, such as cyclones, droughts, and floods, can increase their workload and have a negative influence on their education and economic opportunities, as they are often the first to drop out of school or lose their jobs during times of environmental distress. This can further deepen the vicious cycle of poverty and worsen the social and cultural constraints faced by women (Gomes et al., 2022). Eastin (2018) reported that lower levels of women's social and economic rights are seen in US states with more temperature variability and an increase in the frequency of extreme weather events. Similarly, there are age-based stratifications in health hazards associated with extreme weather events and their associated diseases (Cutter, 2017).

According to Ngepah & Mwiinga (2022), long-term shifts in temperatures and weather patterns would lower the likelihood of employment more for men than for women, but extreme weather occurrences, driven by climate change, have a greater negative impact on female employment prospect. Lecoutere et al. (2023) observed that gender inequality caused by climate change and extreme weather events is linked to gendered roles such as agriculture or industries with existing institutional constraints that limit women's participation. Shayegh & Dasgupta (2024) explained that, while high-skilled labour is unresponsive to climate change impacts, higher temperatures have a negative influence on working hours for low-skilled labour, particularly among women in highly exposed industries.

Apart from impacting labour productivity (Tsigaris & Wood, 2019), climate change has the potential to cause widespread wealth redistribution which further compounds its impacts on vulnerable groups (Fenichel et al., 2016). Bastien-Olvera et al. (2023) underlined that the consequences of climate change impacts on human welfare remain unclear, since they depend on the nature of the changes, the value of the impacted benefits and the extent to which people rely on natural systems for their wellbeing. This necessitates the need for adaptive policies which prioritise flexibility, responsiveness, and continuous learning, enabling policymakers to handle the dynamic and uncertain nature of climate change, its associated extreme weather events, and their consequences.

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2.3. Preliminary information on Selected studies

2.3.1. Geographical scope of reviewed studies

The selected sample includes country-level, city-specific, regional, Europe-wide, and Europe-inclusive global studies. A graphical illustration is presented in Figure 3.

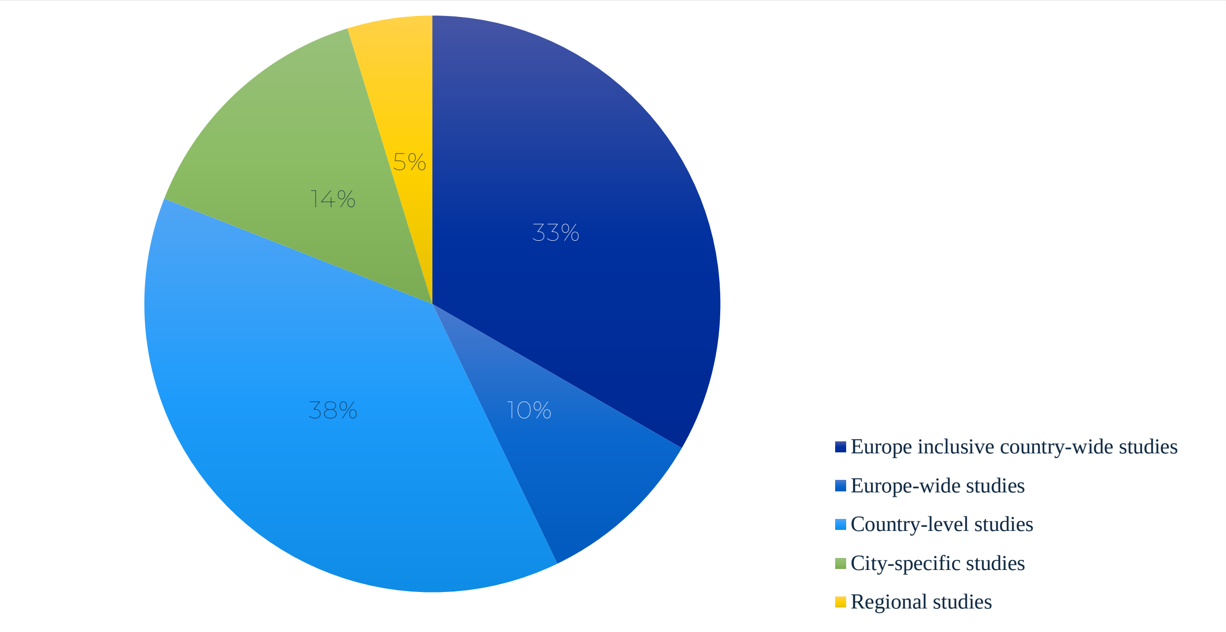

Figure 3 Graphical distribution of reviewed studies by geographical focus

A large proportion of the selected research (38%) were country-level studies focusing on the Czech Republic, Spain, Portugal, and Germany. City specific studies account for 14% of the sample. Regional studies (5%) concentrate on European Union and Southern Europe countries, whereas Europe-wide research (10%) include all of Europe. Global research that includes European countries in the panel also make up a major component of the selected sample. This distribution demonstrates the possibility for future research expansion in Europe-specific studies.

2.3.2. Climate and Extreme weather events information

The selected literature in the study have considered either climate related data such as carbon emissions, focused on the impact of certain disasters or disaster data which includes several types of extreme weather events. Figure 4 and Figure 5 give context to this information for the reviewed literature.

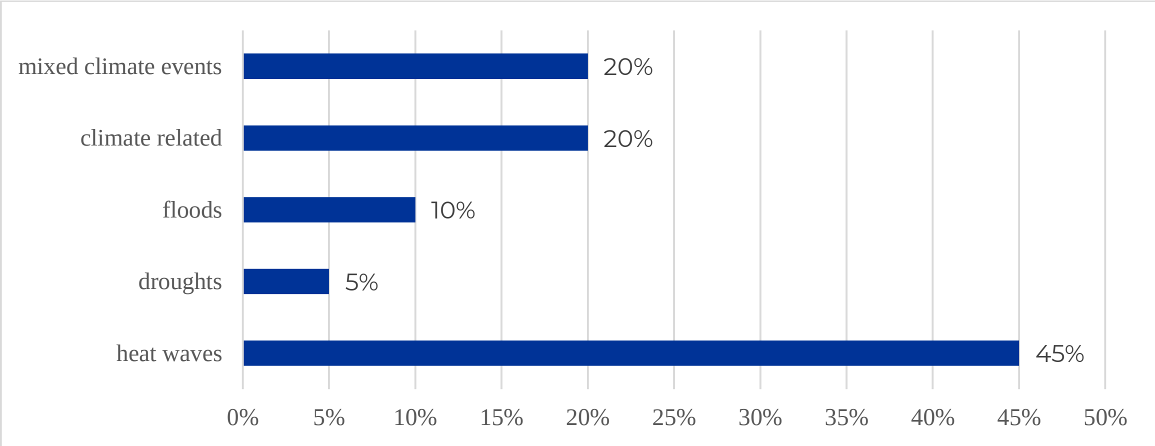

Figure 4: Distribution of studies by climate / disaster type

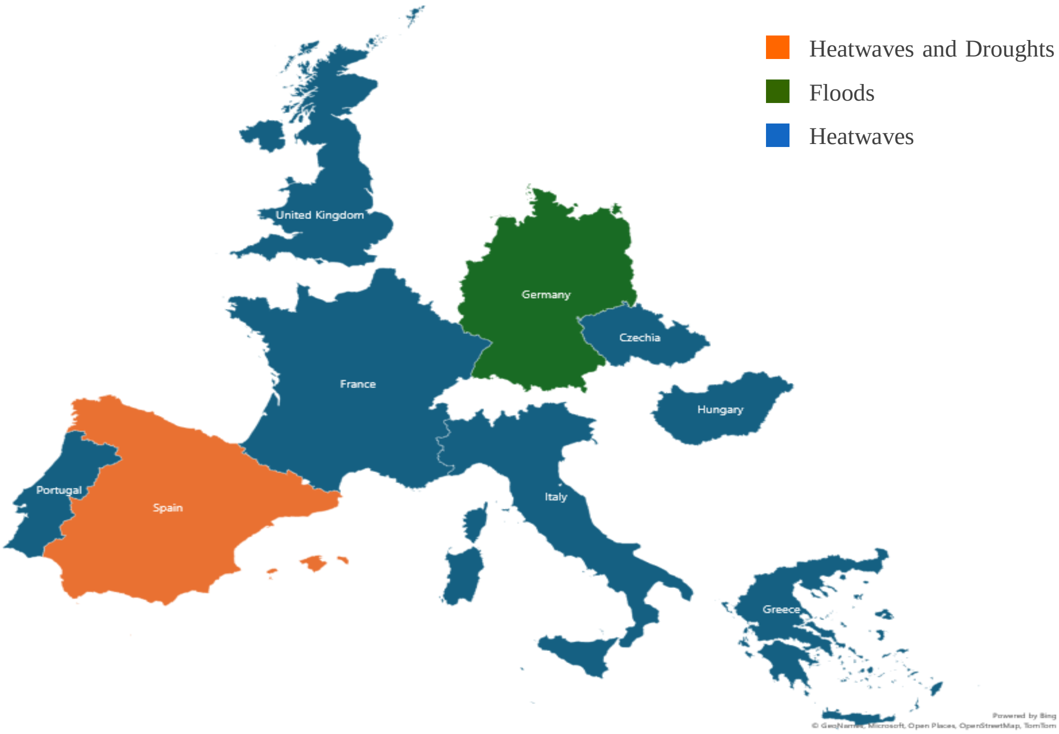

Figure 5: Map of countries covered by extreme weather events type

As seen in Figure 4, the majority (45%) of studies have focused on the impact of heatwaves as a climate change related event. These studies cut across several European countries such as Spain, Portugal, Greece, Hungary, United Kingdom (England), Italy, Czech Republic (Czechia) and France. 10% which consider flood damages focused on Germany, and 5% drought related studies were about Spain. 20% which utilised climate related data such as carbon emissions, mixed climate events or broader disaster data that include different events such as flooding, landslide, rockfall, beach retreat, coastal erosion, etc. centre broadly on Europe or

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regions within Europe. A map of the extreme weather events covered in different regions are shown in Figure 5.

2.4. Perspectives from multi country studies – Europe inclusive

Studies have also examined the impact of climate change induced disasters on existing inequalities from a cross-country perspective. Cevik & Jalles (2023a) used a VAR model to show how climate change affects income inequality in 158 countries. Accounting for demographic and economic factors in individual countries, they discovered that while climate change increases income disparity, the effect is statistically insignificant in developed countries. They noted that low levels of adaptation and mitigation in developing countries increases the negative effects of climate change. Applying a fixed effects model to a panel of 101 countries, Palagi et al. (2022a) stated that the negative consequences of climate change are stronger in agriculture-intensive countries than non-agriculture-based countries. Likewise, Paglialunga et al. (2022a) highlighted the importance of the agricultural sector in climate change adaptation and mitigation. They stated that rising temperatures and income disparity affect workers in rural areas and highly populated countries.

Cappelli et al. (2021a) estimated the interconnectivity of natural disasters and inequality on a panel covering 149 countries. Applying the three stage least square technique on vulnerability and Gini coefficient, their study showed that higher levels of income inequality are associated with people who are more affected by natural disasters. Yamamura (2015a) examined the effect of natural disasters on income inequality in 86 countries through the fixed effects technique. The study identified two sets of natural disasters, the predictable disasters such as floods and storms and unpredictable disasters such as earthquakes and highlighted that disaster induced inequalities are evident between different areas and socioeconomic status. Using a 5-year average values of Gini coefficients and several disasters between 1970 to 2004, the study showed that natural disasters worsen income inequality in the short term but not in the long term due to the redistribution of wealth from non-affected to affected areas.

Neumayer & Plümper (2007a) stated that women are disproportionately affected by disaster related deaths rather than their male counterparts. Using a random effects model on a panel of 140 countries, they argue that natural disasters reduce women's life expectancy disproportionately because these events exacerbate existing socioeconomic inequalities and discriminatory practices that make women more vulnerable to death, both immediately and in the aftermath of the disaster creating gender gaps in life expectancy change driven by natural disasters. They noted that these differences could be mitigated by improving the socioeconomic status of women. In contrast, Nguyen & Nguyen (2023a) used the fixed effects model to analyse how natural disasters influence gender disparities in a panel of 130 countries and found that natural disasters have more negative effects on men's health than on women. However, they reported that women are more disproportionately affected in terms of employment, wages, and salaries.

Table 1: Summary of reviewed panel studies – method, data, scope and sources

Author	Method	Inequality / Climate related data	Sources	Scope
Cevik & Jalles (2023b)	Vector Autoregressive Modelling	Gini Index, GDP-adjusted climate change vulnerability index	Standardised World Income Inequality Database (SWIID) Notre Dame Global Adaptation Institute (ND-GAIN)	1995 - 2019
Palagi et al. (2022b)	Fixed effects	within-country income distribution Temperature and Precipitation Climate Variables	World Inequality Database World Bank Climate Change Knowledge Portal	1980 - 2010
Paglialunga et al. (2022b)	Fixed effects	Gini index Temperature and Standardised Precipitation Index	SWIID UEA - Climatic Research Unit (CRU)	2008 - 2017
Cappelli et al. (2021b)	Seemingly Unrelated Regression (SUR)	Gini Index Climate-related natural disasters	SWIID Emergency Events Database (EM-DAT)	1992 - 2018

Author	Method	Inequality / Climate related data	Sources	Scope
Yamamura (2015b)	Fixed effects	Gini Coefficient Number of natural disasters	SWIID EM-DAT	1965 - 2014
Neumayer & Plümper (2007b)	Random effects	Gender-gap in life expectancy Disaster Mortality	International Data Base (IDB) EM-DAT	1981 - 2002
Nguyen & Nguyen (2023b)	Fixed effects	ratio of female to male waged employment and self-employment, life expectancy at birth, ratio of survival, gender parity index for school enrolment, Women Business and the Law Index Score Susceptibility Index	World Development Indicators (WDI) World Risk Report	- 2019

2.5. Perspectives from Europe specific literature

Various studies have assessed the economic consequences of climate change and extreme weather events in Europe, highlighting the disproportionate impact between and within countries (Mateos et al., 2023). Studies have highlighted the profound implications of extreme weather events on health and well-being and their potential economic consequences (Bosello et al., 2012; Cardil et al., 2014). Its microeconomic implications for labour, productivity and asset accumulation in firms have also been investigated (Leiter et al., 2009; Noth & Rehbein, 2019). Koks et al.

(2019) using flood data across Europe, showed how the negative consequences of disasters spread beyond affected regions due to interconnected trade networks. There is a growing recognition of the importance of considering social equity in climate change adaptation and mitigation efforts (Aakre & Rübbelke, 2010; Ganzleben & Kazmierczak, 2020). Research in this area examines how climate change impacts intersect with existing social inequalities, disproportionately affecting marginalised communities.

Vrontisi et al. (2022) evaluated the macroeconomic impacts of climate change on the Blue Economy of nine southern European islands (Azores, Baleares, Canaries, Crete, Cyprus, Malta, Madeira, Sardinia, and Sicily), using a model-based approach. They noted that island communities are among the most severely impacted by global climate change due to their isolated geography, extensive coastlines, and limited economic diversification. The study considered climate change impact chains on tourism, maritime transport, and electricity demand within a downscaled modelling framework across various climatic scenarios projected to the end of the century. Their findings indicate significant economic losses across all scenarios. However, the extent of these impacts varied among islands, influenced by their level of economic diversification and geographic remoteness. The tourism sector, crucial to island economies due to its complex value chain and substantial contribution to value added, is particularly affected. Additionally, the increased electricity demand for cooling and water desalination exacerbates the economic strain on these islands.

Using actual 2021 flood damage data, Odersky & Löffler (2024a) investigated the effects of natural disasters on various income categories in locations near impacted rivers. By linking official geo-coded satellite data on flood-affected structures with neighbourhood-level socio-economic information, the study analysed the empirical relationship between flood damages and household income. A panel regression model which incorporated regional fixed effects was used to assess exposure differentials. Their findings revealed that the household income of flood affected neighbourhoods were on average 3% lower than non-affected areas. Also, they discovered that individuals in the impacted areas who were in the bottom 60% of the income distribution were three times more vulnerable than households in the top 40%. They stressed the regressive nature of climate change vulnerability and the disproportionate impact of natural disasters on low-income German communities.

Similarly, Tovar Reaños (2021) evaluated the distributional effects of floods in Germany across different types of households and income levels. The study used simulations and regression techniques to investigate the relationship between several flood waves in Germany between 1993 and 2013 and the Atkinson inequality index. The empirical findings suggest that the resulting economic costs associated with flood disasters exacerbate income inequality. Flood disasters disproportionately affect low-income households, with the greatest impact on families with dependent children and households with a person over the age of retirement. The recovery process following a flood can exacerbate inequality since more affluent households have better access to recovery mechanisms, such as insurance coverage, allowing them to get back on their feet faster than those without (Tesselaar et al., 2020).

Quiroga & Suárez (2016a) studied the impact of climate change and droughts on the average income distribution in rural Spain. They focused their research on the agricultural sector, examining drought hazards in ten river basins and their impact on the distribution of agricultural-based income. Using the Olley-Pakes method, which employs the ordinary least squares and instrumental variable estimation techniques, they demonstrate that droughts exacerbate rural farmers' income disparity. They did, however, emphasise the unequal nature of the impact depending on farm location and crop type. They observed that crops such as olives are more vulnerable due to the labour-intensive nature of their cultivation than grapes, which are technology-intensive, providing implications for future adaptation policies for rural farmers.

Studies have also shown that gender inequality issues are exacerbated by natural disasters. Vésier & Urban (2023a) examined the relationship between daily temperature and mortality in the Czech Republic from a sex and gender perspective. They considered factors like age and marital status in determining heat-related mortality risks. Data between 1995 and 2019 which accounted for the five warmest months in the country (May to September) were analysed using a quasi-Poisson regression model with a distributed lag non-linear model (DLNM) to account for delayed and non-linear temperature effects on mortality. The study found that women, particularly those over 85 years old, are more vulnerable to heat-related mortality risks than men. The critical temperature threshold is 16.2°C for women and 20°C for men. Married individuals had lower mortality risks compared to single, divorced, and widowed individuals, with divorced women at significantly higher risk than divorced men. They underlined that men were most at risk between the ages of 75 and 84, and when they were widowed.

Navas-Martín et al. (2022) suggested that the rise in Spain's temperature since pre-industrial times have increased the intensity and frequency of heatwaves that significantly impact public health. By analysing the minimum mortality temperature (MMT) for men and women from 1983 to 2018, they found different effects across provinces and genders, with an average MMT of 29.4°C for men and 28.7°C for women. Although the results showed that women were more vulnerable to extreme heat than men, they found that women adapted to heat faster. Guliyev (2023b) investigated unobserved factors that influence gender inequality across 41 European countries from 1990 to 2020 using the Fixed Effects Spatial Autoregressive with Spatial Autoregressive Disturbances through the Gender Inequality Index heatmap and the Moran's I spatial autocorrelation test. Accounting for unobserved factors such as life expectancy at birth, years of schooling, democracy index, shared culture, beliefs, and values which significantly contributes to spatial effects and gender inequality, the study noted that higher carbon emissions increase the later.

Capetillo-Ordaz et al. (2024) considered the effects of climate change on gender inequality from gendered energy-vulnerability. The study highlighted that energy poverty is a growing concern within the European Union (EU), adversely affecting the well-being and social inclusion of vulnerable populations, especially women. Using a case study of Madrid, Spain, the study presented maps gendered energy vulnerable areas in the EU using a gender-responsive index. It leveraged open access data to evaluate energy vulnerability from a gender perspective and cross-references previous energy poverty assessments to identify corresponding cases of gendered energy vulnerability, resulting in a Gendered Energy Vulnerability Index (GEVI), which classifies areas based on their risk of experiencing gendered energy vulnerability. The findings revealed that 42 neighbourhoods, or 32% of the city, are at risk of gendered energy vulnerability. This risk predominantly affects elderly women, single-parent households led by women, and women engaged in part-time employment or elementary occupations.

Under the framework of the EuroHEAT project, D'Ippoliti, Michelozzi, Marino, De'Donato, et al. (2010) evaluated the impact of several heatwaves' episode between 1990 and 2004 in Athens, Barcelona, Budapest, London, Milan, Munich, Paris, Rome, Valencia by age groups, gender, and other characteristics. Using generalised linear models, they noted that females are more susceptible to disaster deaths than male, especially in the mediterranean cities. Inés et al. (2012) used generalised linear models to study the mortality and rising temperature nexus in Cantabria, Spain, and found that higher temperatures resulted in higher fatality rates. The study found that a 1°C increase in maximum temperature leads to a 2% increase in mortality, whereas a 1°C increase in minimum temperature leads to a 2.5% increase. However, the effect is more in women than in males, particularly for minimum temperature.

Using a Poisson regression model, Marí-Dell'Olmo et al. (2019a) examined the impact of heatwaves on death rates in Barcelona between 1992 and 2015. In general, they discovered that women were more likely than men to die from exposure to high temperatures. Stratifying by age groups, they found that while there are more deaths among women (48.8%) than males (24.6%) in the oldest age group (≥ 85 years), there are fewer deaths among men (19.3%) between the ages of 25 and 64. Ellena et al. (2020a) used time series regression with distributed lag non-linear models to investigate socioeconomic inequalities caused by rising temperatures in Turin and discovered that mortality risk is higher among women. Similar findings also apply to Portugal where heatwaves were responsible for 79% of increases in mortality among women, a significantly larger percentage than that of males (41%) and Galicia, Spain, where women are thought to be more vulnerable to the effects of heatwaves than men (Trigo et al., 2009).

Table 2: Summary of reviewed Europe specific studies – method, data, scope, and sources

Author	Method	Inequality / Climate related data	Sources	Scope
Albu & Albu (2020)	Two stage least squares and Fixed effects	Gini Coefficient Carbon Emissions	Eurostat Database	2000 - 2018
Odersky & Löffler (2024b)	Fixed effects	Average annual disposable income Satellite data on flood damages	Leibniz Institute for Economic Research EU's Copernicus Emergency Management Service	2021
Reaños (2021)	Probit regression and three stage least square	Atkinson Inequality Index Flood related variables	German Survey of Income and Expenditure Eval-MAP dataset	2012 - 2015
Quiroga & Suárez (2016b)	Ordinary least squares and Instrumental variables	Gini Coefficient decomposition Standardised Precipitation Index/Palmer Drought Severity Index	SABI database (Iberian Balance sheet Analysis System) AEMET (Spain State Met. Agency)	1990 - 2013
Vésier & Urban (2023b)	quasi-Poisson regression and distributed lag non-linear model	Daily mortality Daily average temperature	Institute of Health Information and Statistics of the Czech Republic	1995 - 2019

Author	Method	Inequality / Climate related data	Sources	Scope
			Czech Hydrometeorological Institute	
Navas-Martin et al. (2022)	Multi-level linear regression	Daily mortality Maximum daily temperatures	National Statistics Institute State Meteorological Agency	1983 - 2018
Guliyev (2023a)	Fixed effects / Quasi maximum likelihood estimator	Gender Inequality Index Carbon emissions per capita	Human Development Reports – UNDP Global Carbon Project	1990 - 2020
D'Ippoliti, Michelozzi, Marino, de'Donato, et al. (2010)	Generalised linear models	Mortality data air temperature, dew point temperature, sea level pressure, total cloud cover, wind speed and wind direction	Euro HEAT Project	1990 - 2004
Acebo et al. (2012)	Weighted and Poisson regression	daily numbers of deaths Temperature	Spanish Institute for Statistics Spanish Meteorological Agency	2003 - 2006
Marí-Dell'Olmo et al. (2019b)	Poisson regression and distributed lag non-linear model	daily counts for natural mortality Daily maximum temperatures	Mortality registry of Barcelona Servei Meteorologic de Catalunya" (METEOCAT)	1992 - 2015
Ellena et al(Ellena et al., 2020b)	Poisson regression and distributed lag non-linear model	Number of deaths Daily summer temperatures	Turin Longitudinal Study MESCAN-SURFEX system	1982 - 2018

2.6. Findings and conclusions from the literature review

2.6.1. From multi countries studies

The empirical literature strongly supports the hypotheses that climate change and extreme weather events are associated with rising wealth, income, and gender inequalities. Country-wide studies have focused on its impact on inter-country inequalities, differentiating between developed and developing countries. Several of these studies conclude that although developing and developed countries suffer the adverse impacts of climate change and extreme weather events, these impacts are not same for all countries. They note that compared to developed countries, developing countries have less availability of technologies, poor infrastructure resilience and mitigation efforts, making them more vulnerable to the adverse effects of climate change. It is noted that countries with greater degrees of inequality and more frequent cases of extreme weather disasters may become stuck in a poverty cycle.

Studies have examined the extent of these effects in terms of demography distribution and sectoral reliance. They emphasise that climate change and extreme weather events increase inequalities in countries where a large share of the population live in rural areas and rely largely on primary industries, such as agriculture. Rising temperatures or precipitation hinder economic development and exacerbate existing inequalities in agriculturally intensive countries, where a major part of the population works in agriculture and related sectors. They also state that the magnitude of these effects would vary based on the type of agricultural activity and the crop's sensitivity to temperature changes. Similarly, they emphasise that low-income earners and disadvantaged groups in cities are more vulnerable to flooding due to the poor quality of their homes and concentration in prone locations. Furthermore, their inability to afford insurance and get compensation in the event of a disaster makes them more vulnerable to climate change hazards.

Country-wide studies also consider the impacts of climate risks on gender inequalities in countries. Channels of impacts include employment, education, and health status. These studies show that disasters have a more negative impact on women's employment than men's, particularly in low-income countries than high-income countries. Also, the resulting reduction in income decreases the chances of women education who are considered crucial support systems in difficult times, indicating the influence of physiological, cultural, or religious factors. Different opinions on the influence of natural disasters on health status are presented. However, in general, women tend to suffer more than men negative effects of climate change in developing countries, but this difference diminish with socioeconomic improvements.

2.6.2. Europe-specific literature

The existence of socioeconomic risks from climate change and extreme weather events is widely acknowledged in Europe-specific studies. These studies have focused generally on climate change or more specific disasters such as floods and heatwaves. Diverse perspectives exist depending on the sector considered, nature and economic strength of the analysed countries. Richer countries within Europe are less vulnerable to the adverse effects of natural disasters than the less developed countries. Similarly, poorer neighbourhoods and low-income households within a country are on average more affected by extreme weather events than richer neighbourhoods and high-income households. The literature also suggests that households in affected neighbourhoods are less likely to afford and have insurance, increasing their vulnerability.

According to studies that evaluate specific sectors within a country, income inequalities are because of the economic damages triggered by climate change and extreme weather events. The literature cites the example of tourism-related industries and the agricultural sector. Because tourism-related industries are labour-intensive, disasters limit economic activity and put pressure on the labour market, resulting in lower earnings, unemployment, and increased income inequality. Similarly, agricultural activities are generally labour intensive, factors like temperature, precipitation, and drought can impact agricultural yield and reduce the income of those employed in the sector. These studies emphasise how their inadequate economic diversification and geographic remoteness exacerbate their inability to adapt and make them less resilient to the effects of climate change.

Climate change and extreme weather events have also been shown to be uneven and regressive in affected areas. Odersky & Löffler (2024a) report a 3% income gap between impacted and unaffected households, and Reanos estimates a 0.14% increase in income inequality among German households. Its influence varies by sector, based on crop variety and proximity to the impacted areas. According to studies, neighbourhoods closer to disaster-prone areas are more vulnerable than those further away. Likewise, certain crops are more resistant to climate changes like flooding than others. As a result, impacted families closest to critical areas would have a greater drop in income than affected households that are farther. Equally, farmers with more resilient crops will see a lower income decline than farmers with less resilient crops.

The reviewed studies also evaluate the impact of climate change and extreme weather events on gender disparities, focusing on mortality and energy vulnerability. These studies suggest different vulnerability levels between men and women to extreme temperatures, with women being more affected than men. Inequalities between genders were also examined through different categorisations such as age and marital status. However, similar conclusions were made, with older women and divorced women being more vulnerable to climate heat induced deaths, at varying percentages in different locations. These outcomes are presented in figure Figure 16. Similarly, in terms of energy vulnerability, women were also considered to be disproportionately affected than men, especially in the elderly, lone-parent, part-time employment, and elementary occupation categories.

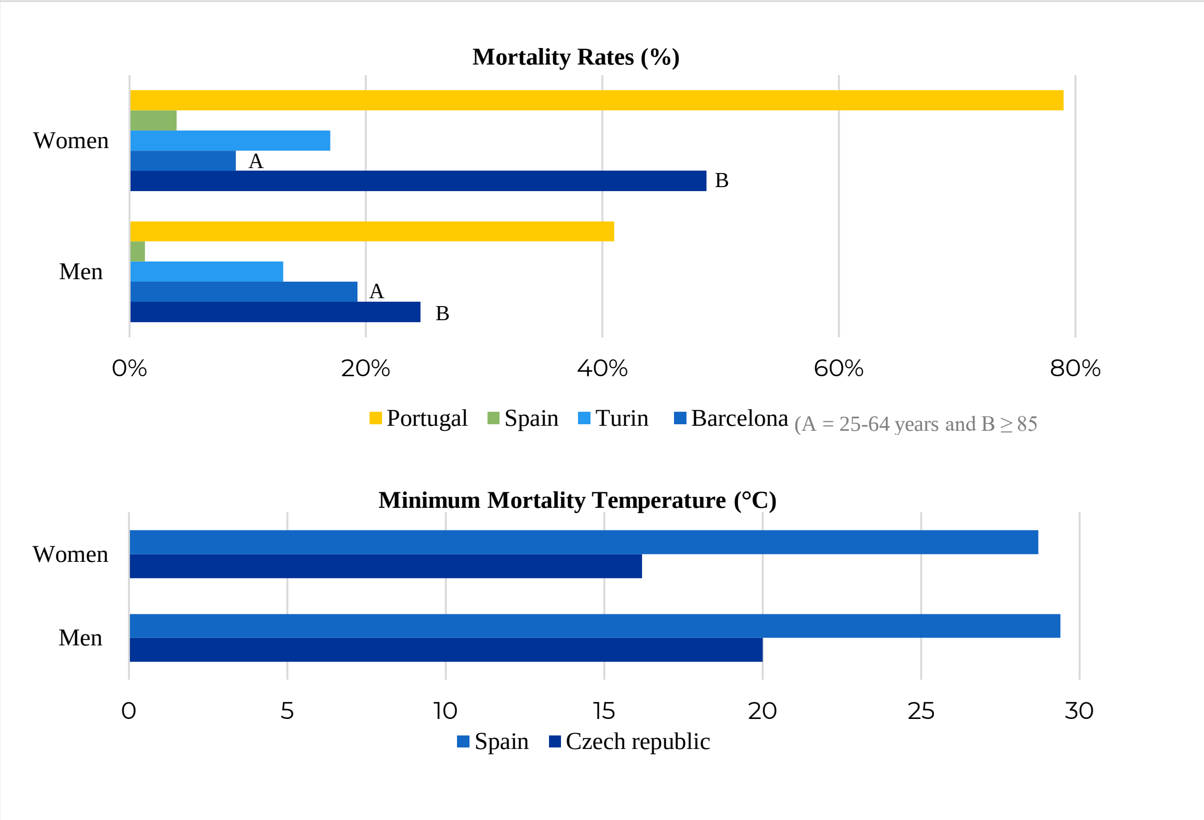

Figure 6: Schematic representation of gender inequality impacts by gender and location

These studies show that gender disparities in climate impacts are amplified by existing physiological, socioeconomic and cultural factors. Women are more vulnerable to high temperatures due to their physiological traits which can be heightened during menopause. Also, existing gender salary gaps, women's low involvement in professional jobs, and a higher possibility of unemployment due to family duties may result in a lower overall quality of life and a greater risk of isolation and poverty in their older years. Furthermore, gender disparities are intricately tied to societal and cultural norms. Geographic disparities in gendered vulnerability to health outcomes are also acknowledged. They propose that education, improved access to healthcare, women's empowerment, and social and cultural reforms can reduce gender disparities in climate change consequences and increase adaptation ability. Figure 7 shows a concise summary of the findings from reviewed studies.

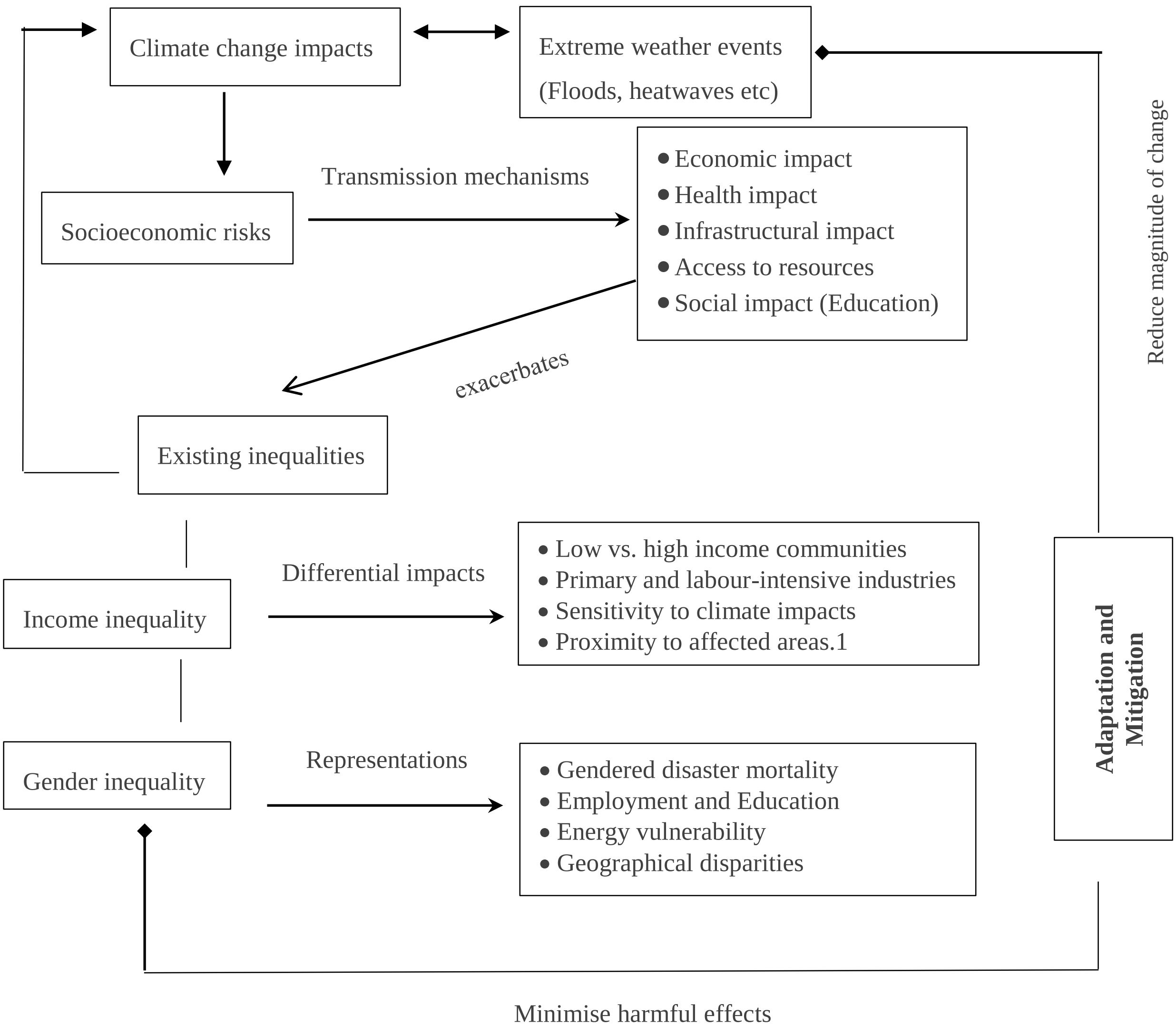

Figure 7: Simplified illustration of findings

3. CGE Modelling of Climate Change impacts on Agriculture

3.1. Basic Structure of CGE Models

CGE models provide a comprehensive, economy-wide framework for assessing how shocks transmit through various agents (e.g., households, firms, and governments) and economic markets (product, factor, and trade markets), with the Social Accounting Matrix serving as the core data structure that systematically records all income and expenditure flows among these actors. Building on this foundation, agriculture-focused CGE models are designed to capture the unique production characteristics, input dependencies, and regional heterogeneity of the agricultural sector. Early work by Adelman & Robinson (1978) introduced agriculture as a core sector linked to households and labour markets to assess policy impacts. Subsequent applications in the late 1970s and early 1990s clustered key methodological contributions—technical change and CES-based input specification (Kaneda, 1982); tax policy effects on land-using sectors (Boyd & Newman, 1991; Hertel & Tsigas, 1988); trade liberalization under alternative macro-closures (Kilkenny & Robinson, 1990; Robinson, 1990); free-trade area simulations (Burfisher Mary et al., 1992); agriculture-driven development strategies (Adelman, 1984).

Agriculture-focused CGE (Agri CGE) models systematically integrated nested CES production functions to represent the complex substitution dynamics among key agricultural inputs—land, labour, capital, and intermediates—within a general equilibrium framework (Boyd & Newman, 1991; Burfisher Mary et al., 1992; Hertel & Tsigas, 1988; Kaneda, 1982; Robinson, 1990). This modelling approach has since become a cornerstone of agricultural CGE analysis, enabling rigorous assessments of how production systems respond to a wide array of drivers, including price shifts, resource endowment changes, policy reforms, and emerging challenges such as climate change. A key enhancement in contemporary agri-CGE models is the differentiation between irrigated and rainfed systems, allowing for biophysical and regional differentiation in input use, technologies, and climate vulnerabilities. Berrittella et al. (2007) developed an early global CGE model incorporating water through the GTAP-W framework, employing a Leontief production function with fixed input proportions, where sectoral water demand responded to water scarcity via a rent mechanism. Building on this foundation Calzadilla et al. (2011) enhanced the model by adopting a more flexible three-level nested CES production structure. In this revised framework, water and irrigable land are first combined into an irrigated land-water composite, which is then integrated with other primary factors in a value-added nest, allowing for a more dynamic representation of water-land interactions under varying climatic and policy conditions.

Another crucial dimension for capturing agricultural realities in CGE models involves addressing spatial heterogeneity. To further capture this, many contemporary agri-CGE models incorporate disaggregation by agro-ecological zones (AEZs) and river basins. Nelson et al. (2009) incorporated AEZs into the IMPACT and Global Trade Analysis Project (GTAP) frameworks by aligning agricultural production systems with AEZ-specific biophysical characteristics, enabling more accurate simulation of region-specific climate impacts on crop yields and land use. Rosenzweig et al. (2014) coupled AEZ-based crop models with CGE to assess how variations in agro-climatic zones influence global food security outcomes under climate change. Britz & Roson (2019) further demonstrated the flexible integration of GTAP-AEZ modules within their G-RDEM recursive dynamic CGE model, supporting long-term, spatially explicit climate impact assessments on agriculture and enabling more nuanced projections of land-use and production dynamics across AEZs.

To comprehensively capture the short- and long-term responses of agricultural systems to various shocks, Agri-CGE models employ both static and dynamic approaches (Babatunde et al., 2017; Ianchovichina & Walmsley, 2012). Static (comparative-static) models contrast two steady-state equilibria—pre- and post-shock—while holding capital stocks and other state variables fixed. They yield insights into ultimate welfare impacts but omit adjustment paths, transition costs, and the timing of resource reallocation. In contrast, dynamic CGE frameworks introduce time explicitly. These can be categorized into recursive-dynamic specifications, which solve sequential static equilibria across periods and update capital stocks, labour endowments, and technological change through accounting identities, and forward-looking, intertemporal models, which embed optimization over multiple periods, allowing agents to anticipate future prices, policies, and climate events when making today's decisions (Bergman, 2005; Dixon & Parmenter, 1996; Ianchovichina & Walmsley, 2012).

Dynamic agri-CGE models thus trace how transient shocks (e.g., droughts) and gradual trends (e.g., escalating water scarcity or phased policy reforms) unfold over time. In doing so, they account for capital accumulation decisions—where investment in physical assets adjusts based on both historical returns and future expectations (Babatunde et al., 2017; Devarajan & Go, 1998; Paltsev, 2004; Thurlow, 2004)— and capture how labour migration patterns and growing populations exert pressure on land use and resource demands, feeding back into agricultural output and food prices. By capturing detailed adjustment paths and path dependencies, dynamic agri-CGE models provide a robust framework for analysing how shocks and long-term trends propagate through investments, prices, land use, and broader system dynamics under evolving economic, demographic, technological, and climatic conditions, demonstrating the capacity of dynamic CGE frameworks to trace investment pathways, amplify adjustment costs via path dependencies, and assess the role of anticipatory technology adoption in mitigating land-use shifts (Babatunde et al., 2017; Bosello et al., 2012; Ianchovichina & Walmsley, 2012).

3.2. Integration of Climate Change Impacts in CGE Models

CGE models assess the economic impacts of climate change on agriculture by converting biophysical outputs into economic parameters that reveal how changes in climate conditions propagate through supply, demand, and trade to affect welfare and income. Rather than directly parameterizing raw climate variables (e.g., temperature, precipitation, or solar radiation) as inputs, CGE approaches rely on a tiered modelling framework that translates spatially and temporally heterogeneous biophysical climate impacts into calibrated economic shock parameters. In practice, this process takes outputs from biophysical analyses—such as climate projections from General Circulation Models (GCMs), crop yield simulations from crop-growth models, and hydrological assessments of water availability—and converts them into adjustments in productivity, input costs, or resource endowments within the CGE framework (Nelson et al., 2014; Wei & Aaheim, 2023). Within this literature, studies can be grouped according to their primary linkage strategy: (i) productivity shocks, (ii) factor endowment shocks, and (iii) fully integrated frameworks that combine both.

Early applications focused predominantly on productivity shocks. For example, Juliá & Duchin (2007) translated literature-derived estimates of yield declines into identical, Hicks-neutral Total Factor Productivity (TFP) cuts for grains and livestock. By imposing a uniform adjustment across all regions and commodities, this approach precludes differentiation of agro-climatic conditions and crop-specific responses, limiting the model's representation of spatial heterogeneity and yield variability essential for policy-relevant analysis.

Subsequent efforts introduced factor endowment shocks alongside or instead of productivity adjustments. Calzadilla et al. (2011) used HadGEM1-TRIP outputs—linking climate projections with river flow simulations—to derive distinct productivity multipliers for rain-fed and irrigated land, while also imposing irrigation-water endowment shocks in GTAP-W across eleven regions. Calzadilla et al. (2014) then adapted this framework to a South Africa case study, layering climate-driven yield shocks with a 22% productivity increase and doubling irrigated area; these changes were implemented through productivity adjustments and shifts in land allocation under constrained water availability. Building on these foundations, Sartori et al. (2017) integrated GAEZ-based, crop-level yield damage and LUISA's subnational land-supply projections into a GTAP9-based, EU28-disaggregated model, further improving the spatial precision of both productivity and land-endowment shocks.

Moore et al. (2017) further expanded spatial coverage by using meta-analytic yield estimates and the AgMIP GGCMI ensemble under RCP8.5—including CO_2 fertilization and "true adaptation" effects—to derive region-specific yield-change percentages for maize, rice, wheat, and soybean, imposing these as Hicks-neutral TFP multipliers across 140 GTAP regions and aggregating into 16 regions to inform welfare impact estimates and calibrate damage functions.

The most sophisticated frameworks fully integrate biophysical and economic modules, endogenizing factor endowment effects. For example, Nelson et al. (2014), these frameworks use external crop growth and hydrological outputs to impose exogenous shocks on yields, water availability, and land suitability. They then endogenously adjust land allocation, factor substitution, and technological adoption within the CGE equilibrium, capturing feedback between biophysical constraints (e.g., CO_2 fertilization, irrigation limits) and economic responses (production, trade, welfare). Representing a further evolution in integration, models like MIROC-INTEG-LAND developed by Yokohata et al. (2020) demonstrate advanced coupling of component models. MIROC-INTEG-LAND, for instance, integrates a land surface model with human water management, crop growth, land ecosystem, and an economic activity-based land-use decision model. In this system, detailed water resource and crop yield information iteratively informs land-use predictions. For example, simulated crop yields from the crop growth model affect the land-use model's allocation, whose outputs (e.g., irrigated areas) then influence the land surface and water management model's subsequent calculations. This dynamic, iterative coupling enables more consistent handling of spatiotemporal details and two-way feedback between biophysical processes (like water availability and crop growth) and human responses (like land-use change and irrigation) directly within the integrated system. This approach surpasses using biophysical outputs as mere one-way shocks to CGE models, providing enhanced capability to assess interactions often simplified in conventional IAMs.

Table 3 presents key studies that illustrate various approaches to assess the macroeconomic implications of climate change on the agriculture sector. It summarizes their biophysical or climate data inputs, the types of exogenous shocks imposed, and the corresponding CGE parameters modified. These studies include productivity-impact approaches based on biophysical yield change projections, methods addressing shifts in factor endowments, and strategies for integrating multiple impact pathways.

Table 3: Overview of CGE climate-impact models, input data, shock types, and affected parameters.

Study	Biophysical/climate source(s) fed into CGE	Nature of exogenous shock(s)	CGE parameters affected
Juliá & Duchin (2007)	Literature-based yield-decline estimates (climate scenarios circa 2050) for grains & livestock sectors	Percentage-based, Hicks-neutral TFP reductions for grains & livestock sectors by region (no tariff changes)	Sector-level TFP multipliers for grains & livestock by region; Armington trade elasticities unchanged, allowing endogenous trade
Calzadilla et al. (2011)	Hadley Centre GCM + hydrology module (river runoff)	Change in yields for rain-fed & irrigated crops; Change in irrigation-water supply for each of 11 GTAP regions	Land-productivity multipliers; water-factor endowment by region for 2020/2050
Calzadilla et al. (2014)	Two GCMs x two SRES scenarios (A1B, B1) feeding crop-model outputs	Change in yields (baseline shock); two adaptation scenarios: + 20 % R&D yield boost or doubled irrigated area	Crop TFP shocks; irrigation water & land-factor endowment shocks at South African national scale
Nelson et al. (2014)	Ensemble crop simulations for RCP 8.5 (wheat, rice, coarse grains, oilseed)	Change in average yield (estimated -17%) shock by crop & region	Applied as crop-level TFP shocks in the five global CGE models—AIM/CGE, ENVISAGE, FARM, GTEM and MAGNET—each calibrated to project impacts in year 2050 (by GTAP-region)
Sartori et al. (2017)	Single GCM (Hadley CM3 under B2 SRES) via GAEZ for yields; LUISA Territorial Modelling Platform for projected changes in total agricultural area	Region-specific yield shocks derived from Change in temperature (Hadley CM3/B2 via Roson & Sartori (2016) damage functions); land-endowment	Yield factors for major crops & effective agricultural land supply for Northern, Central, Southern Europe

Study	Biophysical/climate source(s) fed into CGE	Nature of exogenous shock(s)	CGE parameters affected
		changes from LUISA projections to 2050	
Moore et al. (2017)	Meta-analysis of 1 010 point-estimates from 56 studies (Challinor et al. 2014) & AgMIP GGCMI ensemble under RCP 8.5, including CO_2 fertilization	Exogenous percentage-change in yields for four major crops (maize, rice, wheat, soybean) by region for 1–3 °C global warming, incorporating small "true adaptation" effects; shocks represent 2050 yield changes	Hicks-neutral TFP multipliers on the four staple crop sectors in GTAP for each of 140 regions (scaling down land-productivity by the projected yield-loss percentages), then aggregated into 16 FUND regions for welfare/damage-function estimation
Hasegawa et al. (2018)	Grid-cell yield projections driven by five CMIP5 GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M, NorESM1-M) under RCP 2.6 & 6.0, *both with and without CO_2 fertilization effects*	Exogenous percentage-change in crop yields (maize, rice, wheat, soybean, etc.) for each region in 2050 under RCP 2.6 & RCP 6.0 (*no CO_2* vs. *with CO_2*)	Applied as crop-level TFP (land-productivity) multipliers in AIM/CGE for each region's staple sectors (to 2050). Yields are aggregated to the country/regional level via SPAM, then imposed directly in AIM/CGE's production functions
Dissanayake et al. (2019)	Literature-based productivity shocks (Hertel et al. 2010 meta-analysis) for five staple groups (paddy rice, wheat, coarse grains, oil seeds, other crops) in South Asia, with separate values for Sri Lanka & Bangladesh under	Climate-induced Hicks-neutral yield shocks by staple & country (e.g., Sri Lanka rice –15 %, Bangladesh rice –10 %) Adaptation via trade liberalization: 50 % or 100 % ad valorem tariff cuts	Country–crop-specific TFP multipliers that uniformly scale down sectoral productivity by the specified percentages; ad valorem tariff-rate parameters reduced by 50 % or 100 % for the designated commodity flows.

Study	Biophysical/climate source(s) fed into CGE	Nature of exogenous shock(s)	CGE parameters affected
	two scenarios (Low/Medium).	on agricultural flows	
Yokohata et al. (2020)	Five CMIP5 GCM forcings (ISIMIP bias-corrected) via HiGWMAT/PRYSBI2 (yields & water); AIM/CGE (SSP2) demand inputs under RCP2.6/4.5/6.0/8.5	RCP-driven crop-yield & irrigation-water shocks; AIM/CGE-specified demand shocks for food, bioenergy, pasture, and wood	Cropland, bioenergy, pasture, and forest area-demand constraints; land-rent and allocation adjustments in AIM/CGE
Janssens et al. (2020)	Global crop-model yield projections under RCP 8.5	Regional yield shocks by crop; adaptation case: additional heat-/drought-tolerant variety gains	Percentage change in yield vs. baseline) are aggregated to four broad crops and computed for each MAGNET region under RCP 8.5 (2050)

3.3. European CGE models: Data Frameworks and Model Architectures

Currently, a diverse suite of CGE models has been developed for Europe, each calibrated to reflect regional economic structures and policy environments. For each model, four key dimensions are summarized: the benchmark year used for calibration; the spatial resolution, ranging from national-level or sub-national (e.g., NUTS-2) granularity up to multi-region aggregations; sectoral aggregation (including any enhanced breakdown of agricultural or industrial sub-activities) and the number of representative household groups (e.g., income deciles, rural versus urban); and the treatment of international trade (e.g., Armington assumptions, nested CES structures, or bilateral trade matrices). Any sectoral detail enhancements (e.g., explicit modelling of irrigation systems, land-use categories, or green technologies) are highlighted, along with each model's typical applications (e.g., assessing Common Agricultural Policy reforms, evaluating carbon pricing impacts). Table 4: Overview of Prominent CGE models for Europe provides an overview of prominent CGE models for Europe, detailing their coverage, key structural characteristics, and main policy application areas.

Table 4: Overview of Prominent CGE models for Europe

Model name	Coverage	Key Structural Characteristics	Main Policy Application Areas
ICES	Global (around 45 regions, typically; EU can be disaggregated into up to 125 NUTS-2 regions)	Recursive dynamic, multiregional CGE model, calibrated to the GTAP database. It incorporates exogenous climate-sensitive yield shocks, endogenous water scarcity, and disaggregated energy sectors. The model features a nested production structure (Leontief for value-added/intermediate inputs, CES for factor/energy substitution) and a specialized land allocation module.	Assessing economic impacts of climate change (e.g., sea-level rise, heatwaves) and evaluating adaptation strategies; analysing climate policies and mitigation efforts (e.g., decarbonization pathways, carbon markets); supporting studies on sustainable resource management (e.g., water economics and policy); examining economic consequences of geopolitical events; exploring trade dynamics.
GEM-E3	All EU member States, OECD, G20 (individually), 19 major economies (RoW)	Global, multi-sectoral, recursive dynamic, integrates micro-economic behaviour, detailed GHG emissions/abatement, CES production, Armington assumption	Energy, Climate, Air Quality policies (e.g., 2030 Framework, Paris Agreement, Clean Air Package, decarbonization scenarios, oil price shocks, fiscal policies)
MIRAGE	EU Member States (27), Global (world regions, national, country level)	Recursive-dynamic (comparative-static option), multi-region/sector, top-down, optional imperfect competition, additional Armington nesting, reduced labour mobility	Trade policy (tariffs, NTBs, subsidies), Impact Assessments (ex-ante/ex-post), Sustainability Impact Assessments (SIA), Economic Analyses of Negotiated Outcome (EANO)

Model name	Coverage	Key Structural Characteristics	Main Policy Application Areas
FIDELIO	45 countries (27 EU member states, 18 major trading partners, and one aggregated "rest of the world" region), spanning 64 industries and 64 correspondin g products	FIDELIO is a four-tier framework. It features endogenous investment dynamics, a social accounting matrix for income distribution, and a price-and-behavioural-elasticity general equilibrium system. Key mechanisms include a recursive capital-accumulation identity, nested CES technology, Armington nest for trade, a hybrid Phillips rule for wages, and a Taylor rule for monetary policy.	Assessing socio-economic and environmental impacts of diverse policies (industrial, trade, and innovation initiatives) by providing evidence-based insights on jobs, growth, investments, resource use, emissions, and trade balances across sectors and countries.
RHOMOLO v4	All NUTS-2 regions of the EU	Spatial, multi-sectoral (10 NACE Rev. 2 sectors), optimizing agents, captures trade flows & factor mobility	Human capital, Transport infrastructure, R&D & Innovation, Cohesion policy, public investment/consum ption impacts
EuroTERM	40 countries (mainly Europe); NUTS-2 level for 24 European countries; 328 sub-national regions	Multi-country, sub-national CGE model; based on TERM methodology; 74-sector detail with enhanced electricity sector; multi-tiered trade structure; single representative household per region	Regional impacts of major shocks (e.g. Ukraine war), energy transition and decarbonization, agricultural and environmental policies (CAP, water, land-use, climate), trade policy, infrastructure investments (ports, transport); applied in Nordic regions; potential for tourism modelling

3.3.1. ICES Model

The Inter-temporal Computable Equilibrium System (ICES) is a sophisticated, recursive dynamic, multiregional Computable General Equilibrium (CGE) model that was jointly developed by researchers at the Fondazione Eni Enrico Mattei (FEEM) and the RFF-CMCC European Institute on Economics and the Environment. Calibrated to the GTAP database (latest GTAP 9; see (Bardazzi et al., 2024)), ICES draws upon detailed input–output tables, bilateral trade flows, and sectoral value-added information to ensure that the representation of sectoral costs, trade elasticities, and factor endowments faithfully replicates observed global economic conditions.

ICES employs a flexible regional aggregation scheme, typically defining around 45 regions—each represented by its own household, production, and government agents—to capture global economic interactions. Among these, the European Union region is modelled not only as a single economic bloc but can also be disaggregated into detailed subregions to reflect the EU's policy complexity and diverse climate exposures. In its standard configuration, the European Union functions as one region within ICES, allowing analysis of EU level regulations such as the Common Agricultural Policy, ETS, and renewable energy directives. For finer resolution, the EU can be subdivided into up to 125 NUTS-2 regions, reflecting intra-European heterogeneity in agricultural practices, water stress, energy mix, and adaptation capacity.

Beyond the standard GTAP structure, ICES incorporates exogenous climate - sensitive yield shocks by embedding agronomic damage functions within the agricultural production nest, and endogenous water scarcity by introducing a shadow price for irrigation in regions where hydrological data indicate constraints. Energy sectors are disaggregated to include both fossil and renewable technologies, with cost and efficiency parameters drawn from IEA sources to refine substitution elasticities between energy inputs. To represent government behaviour and fiscal interactions—such as carbon tax revenues, subsidy shifts, and adaptation investment—ICES extends the standard GTAP - based Social Accounting Matrix (SAM) to endogenize public expenditures and transfers, thereby allowing policy shocks to propagate through household incomes and government budget constraints.

Within the general equilibrium core of ICES lies a nested production structure. At the top level, a Leontief function aggregates value-added—which itself is a CES composite of capital, skilled labour, and unskilled labour—and intermediate inputs, allowing the model to capture factor substitution in response to price changes. Energy-intensive sectors feature a distinct CES nest for substituting between fossil fuels (coal, oil, gas) and electricity or renewable energy inputs. In agricultural sectors, a specialized land allocation module assigns total land endowments across crop subsectors, forestry, and pasture based on rent-maximization principles. This structure ensures that, as relative profitability shifts due to climate impacts or policy changes, land use adjusts endogenously.

The ICES model is primarily used to assess the economic impacts of climate change—such as sea-level rise and heatwaves—and to evaluate adaptation strategies (Pérez-Blanco et al., 2022; Standardi, 2023). Additionally, it informs the analysis of climate policies and mitigation efforts—including decarbonization pathways and carbon markets (Moreno et al., 2024)—and supports studies on sustainable resource management, with an emphasis on water economics and policy (Pérez-Blanco et al., 2016). The model also examines the economic consequences of geopolitical events (Auer et al., 2025) and explores trade dynamics (Bosello & Standardi, 2018).

3.3.2. GEM-E3 model

The General Equilibrium Model for Economy - Energy - Environment (GEM - E3), developed by the National Technical University of Athens' E3M - Lab (NTUA/E3M - Lab), is a large - scale, recursive - dynamic CGE model covering 38 regions and over 50 sectors — ranging from disaggregated energy branches and agriculture to services. In contrast to other European CGE frameworks, GEM-E3's distinguishing feature is its comprehensive bottom - up energy module integrated with detailed transmission and distribution capital, enabling more granular assessment of energy - climate interactions while retaining full GTAP calibration for consistent trade and production analysis. It represents individual EU Member States, and aggregated "rest of" blocs to capture global interdependencies (Capros et al., 2013).

The model's database is calibrated to the GTAP framework, ensuring consistency of bilateral trade matrices and SAMs in producer - price terms, which underpins its representation of production, factor incomes, institutional transfers, and trade flows. Dynamics are driven by capital accumulation under myopic agent expectations, with nested CES production functions for firms (capital, skilled/unskilled labour, energy, materials), intertemporal Stone - Geary utility for households (durables vs. non - durables), and a bottom - up energy module covering power technologies (coal, gas, nuclear, hydro, wind, PV, biomass, CCS) integrated with transmission/distribution capital, labour, and materials. Flexible closures allow for alternative assumptions on capital mobility, trade balance adjustment, labour market clearing, and market structures.

An environmental toolkit simulates carbon taxes or tradable permits at various levels, incorporating end - of - pipe abatement cost curves and revenue - recycling options, while welfare impacts are measured via equivalent variation. A stochastic variant (GEM - E3S) further enables Monte Carlo sensitivity analysis on key parameters.

GEM-E3 is widely used across several key thematic areas including Climate Change Mitigation and Economic Assessment (Aleluia Reis et al., 2023), Environmental Policy and Health Impact Analysis, Energy System Decarbonization and Transition Pathways, and Socio-Economic Impact and Vulnerability Assessment.

3.3.3. MIRAGE model

MIRAGE (Modeling International Relationships in Applied General Equilibrium) is a recursive-dynamic, multi-region, multi-sector CGE model calibrated to a GTAP-based benchmark and developed at CEPII in Paris. MIRAGE is overseen by a consortium of leading academic institutions under CEPII's stewardship and undergoes regular recalibration to successive GTAP database editions, refined non-tariff barrier measurements, and updated macroeconomic forecasts, thereby ensuring its continued alignment with the changing global economic landscape. Its geographic coverage extends to detailed country-level representation for all 27 European Union Member States, while other nations can be modelled either individually at the national level or aggregated into broader world regions, enabling flexible spatial resolution depending on data availability and analysis requirements.

MIRAGE extends the GTAP framework by incorporating imperfect competition, an extra Armington nesting layer for quality differentials, and constrained labour mobility, all calibrated to successive GTAP benchmarks and enriched with non-tariff barrier metrics and updated macroeconomic projections; it covers detailed country-level modelling for the EU's 27 member states alongside aggregated world regions over short-, medium-, and long-term horizons, simulating producer and consumer decisions via nested CES and Armington structures, explicitly accounting for capital accumulation, segmented labour markets, and land-use changes, and producing outputs on macroeconomic indicators, sectoral trade and production, emissions, and welfare to inform trade, agricultural, and climate policy analyses, while its detailed calibration and data requirements pose challenges for computational intensity and short-term predictive accuracy.

MIRAGE's applications span ex-ante and ex-post trade policy analyses, sustainability impact assessments, agricultural policy evaluations, climate policy simulations, and services trade liberalization, providing policymakers with projections of economic, environmental, and welfare impacts; while its detailed, recursive dynamic structure and imperfect competition features yield rich insights, the model's extensive data requirements and computational demands can limit short term predictive accuracy, as exemplified by the EU-Korea FTA case study.

3.3.4. FIDELIO model

The Fully Interregional Dynamic Econometric Long-term Input-Output (FIDELIO) model, developed by the European Commission's Joint Research Centre (JRC), in collaboration with partners including the Netherlands Economic Observatory (NEO), the French Economic Observatory (OFCE), and TNO (Netherlands Organisation for Applied Scientific Research). FIDELIO covers 45 countries—including the 27 EU member states, 18 major trading partners, and one aggregated "rest of the world" region—spanning 64 industries and 64 corresponding products.

FIDELIO's framework progresses through four tiers—starting with fixed-coefficient input–output, then endogenizing investment dynamics, adding a full social accounting matrix for income distribution, and culminating in a price-and-behavioural-elasticity general equilibrium system. In the first tier, output in each region is entirely driven by exogenous final demand—intermediate inputs, investment, inventory changes, household and government consumption, and exports—using fixed technical coefficients from the FIGARO tables. The second tier makes investment endogenous via a recursive capital-accumulation identity (investment responds to capital gaps and user costs) while labour demand adjusts gradually toward its cost-minimizing level. The third tier embeds a social accounting matrix so that household income (wages, mixed income, property income, transfers, operating surplus) nets out taxes and funds consumption via a Linear Expenditure or Almost Ideal Demand System, and government revenue (from operating surplus, taxes, contributions) finances debt interest, public investment, transfers, and consumption, maintaining a stable debt-to-GDP ratio. The fourth tier introduces prices and behavioural elasticities: firms minimize costs under a nested CES technology and set mark-up prices, imports follow a two-level Armington nest, households allocate spending based on real income and relative prices, wages evolve via a hybrid Phillips rule, and the central bank follows a Taylor rule. Across all tiers, notional variables (output, prices, wages, factor demands, consumption) adjust with inertia, ensuring convergence to a neo-classical steady state under constant technological progress and population growth.

FIDELIO applications span assessing the socio-economic and environmental impacts of diverse policies—including industrial, trade, and innovation initiatives—by providing evidence-based insights on jobs, growth, investments, resource use, emissions, and trade balances across sectors and countries while capturing complex interdependencies, spillover effects, and new-Keynesian dynamics to support fair and sustainable EU decision-making (Afman et al., 2021; Albizzati et al., 2022; Casas et al., 2025; Rocchi et al., 2019).

3.3.5. RHOMOLO (Regional Holistic Model) V4

RHOMOLO (Regional Holistic Model) V4, also developed by the JRC in collaboration with DG REGIO, is a spatial dynamic CGE model designed for territorial ex-ante impact assessments of EU policies, particularly those targeting cohesion and innovation. Its 2017 dataset underpins all model calibration and simulation work, ensuring that policy evaluations reflect relatively recent economic structures. By capturing regional and sectoral interdependencies, RHOMOLO V4 provides evidence-based scientific support for European policymaking on regional and territorial strategies (García-Rodríguez et al., 2023).

At its core, RHOMOLO V4 is calibrated on interregional Social Accounting Matrices (SAMs) built from the FIGARO tables, which are EU intercountry supply - use and input - output datasets. These national-level SAMs are regionalized to 236 NUTS-2 regions using Eurostat data on gross value added, household income, and employment, supplemented by Structural Business Statistics and transport survey information to estimate interregional trade flows. In the final aggregation, ten broad NACE Rev. 2 industries capture the economic structure, after an initial disaggregation of 64 sectors (later reduced to 56 due to data constraints). Households are represented in each region, with final consumption expenditures regionalized based on income data. Employee compensation is further divided into high, medium, and low skill categories using ISCED 2011 classifications from the Labour Force Survey, while government consumption expenditure is also regionalized. All non-EU regions are consolidated into a single "Rest of the World" entity for trade considerations.

RHOMOLO V4's spatial dynamic framework is recursively implemented, allowing policy simulations over multi-year horizons (for example, a 20-year projection). Trade between NUTS-2 regions is modelled with standard CGE "iceberg" transport costs: a fraction of each good melts away in transit, so that more units must be shipped than arrive (see Persyn et al. (2022) for more details). Final demand—comprising household consumption, government expenditure, gross fixed capital formation, and inventory changes—is first allocated within each region; intermediate demand then draws proportionally on interregional supplies, net of these transport losses. Total Factor Productivity (TFP) shocks can be introduced to explore productivity-driven scenarios, reflecting productivity's central role in projecting regional growth and competitiveness.

The RHOMOLO model is primarily used for comprehensive policy impact assessments across the European Union, quantifying both the direct and indirect economic effects of such policies across EU regions, notably for evaluating EU Cohesion Policy, R&D and innovation policies, and when analysing transport infrastructure, RHOMOLO assesses how reductions in trade costs propagate through inter-regional economic structures, ultimately influencing regional development (Afman et al., 2021; Albizzati et al., 2022; Casas et al., 2025; Rocchi et al., 2019).

3.3.6. EuroTERM model

The EuroTERM model, developed at the Centre of Policy Studies at Victoria University, sources its foundational data from the GTAP master database. Its database has since been updated and is effectively benchmarked to 2017, incorporating figures for regional electricity output, the gross weight of goods handled in ports, economic data for Nordic NUTS-2 regions, and merchandise exports from Europe to the Rest of the World (Wittwer, 2022). EuroTERM covers 40 countries with detailed spatial resolution, including NUTS-2 level disaggregation for 24 European countries, resulting in a total of 328 sub-national regions.

EuroTERM implements a multi-tiered trade structure that differentiates between three distinct layers of trade: intra-national trade between sub-national regions within countries; intra-European trade among the 40 countries represented in the model; and extra-European trade with the Rest of the World (RoW). Inter-country trade flows within Europe are calibrated based on GTAP and Comtrade data, while the spatial distribution of these flows across sub-national regions is allocated using regional activity shares and detailed port throughput data, thereby enhancing the model's spatial fidelity in capturing trade dynamics.

The model's sectoral architecture is grounded in the 65 standard sectors of the GTAP database, with a key structural enhancement being the disaggregation of the electricity sector. Electricity generation is differentiated into nine distinct primary energy sources — coal, gas, hydro, nuclear, oil, solar, wind, waste and other — alongside a separate electricity distribution sector. This results in a sectoral detail of 74 industries and commodities within the EuroTERM database. Industry cost structures and production technologies are calibrated using country-specific GTAP data, under the assumption of uniform technologies across sub-national regions within each country. While the TERM framework supports the incorporation of multiple household types, EuroTERM applications conventionally employ a single representative household per region, with consumption patterns allocated according to the region's share of national labour income, in the absence of further household or demographic disaggregation.

EuroTERM, building on the established TERM methodology, is designed to support a wide range of economic policy analyses that require fine-grained sub-national detail across multiple European countries. Its detailed sectoral and spatial disaggregation enables robust assessment of regional impacts from major events or policy shifts—such as the war in Ukraine or changes in EU-level regulations—as well as energy transition policies, where its disaggregated electricity sector captures region-specific dynamics. EuroTERM has already been applied to Nordic region analyses and offers potential for further extensions into areas such as tourism modelling and comprehensive decarbonization pathways (Wittwer, 2022).

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4. Addressing Gaps in Climate-Economy Modelling of Socioeconomic Risks

This section synthesises insights from the preceding reviews of empirical literature on climate-induced socioeconomic inequalities and CGE modelling approaches, to critically evaluate the methodological limitations in capturing distributional, sectoral, and spatial heterogeneity in climate impact assessments. While CGE models provide a theoretically consistent and internally coherent structure for simulating the propagation of climate shocks through production, trade, and income distribution channels, they often rely on simplifying assumptions that abstract from observed heterogeneity. In contrast, empirical econometric analysis offers robust, data-driven insights into the realised distributional consequences of climate variability and extreme events, capturing structural asymmetries across income groups, sectors, and regions. Taken together, these complementary approaches underscore the need for methodological integration and refinement to more accurately represent the complex, multi-scalar nature of climate-induced socioeconomic risks.

4.1. Empirical Evidence on Structural Inequality and Climate Vulnerability

The literature review (presented in Section 2) revealed the wide range of discussions on the socioeconomic risks of climate change and extreme weather events. Studies have employed different methods in different geographical contexts to analyse how extreme weather events exacerbate existing inequalities. While there exists a large consensus in the literature about socioeconomic risks of climate change, the extent of its impact differs in the long and short term, amongst income, demographic and social groups. Also, while some studies focused broadly on climate change, others have analysed specific weather events such as floods or heatwaves across different regions. Generally, agriculture-related activities appear as a critical pathway for climate change to worsen inequality, both directly and indirectly.

These studies also highlight the critical need for targeted climate adaptation policies to prevent negative impacts and strengthen the resilience of individuals, communities, and countries. They emphasise the need for adaptation policies which improve the socioeconomic status of women in mitigating the gender-biased harmful effects of climate change and extreme weather events. To protect vulnerable communities from the unavoidable effects of climate change and its associated disasters, it is essential to engage in economic diversification and sustainable practices.

Despite extensive studies, research gap exists regarding the socioeconomic risks of climate change after 2021. The papers evaluated cover the years 1965 to 2021, potentially excluding the effects of recent disasters. Europe has suffered severe weather and climatic events since 2021, including heatwaves, droughts, floods, wildfires, and storms. The summer of 2023 was the warmest on record to date, with devastating wildfires destroying more than 460,000 hectares of forests. Similarly, major flood disasters resulting in multiple fatalities and significant economic loss were reported in June 2024. Drought-related agricultural losses were documented in southern and southwestern Europe in 2022, while strong storms with extraordinary wind speeds caused major property damage and accidents across multiple countries. This highlights the need for more recent research into the effects of extreme weather events.

Also, due to the spatial and unequal nature of these negative impacts, policymakers must examine both observable and unobservable aspects to effectively mitigate the repercussions of climate change and extreme weather events. While these studies have empirically established its regressive nature on existing inequalities, it is equally important to differentiate between perceived and actual impacts. More research is needed to understand the subjective and lived experiences of persons affected by natural disasters, including whether, how, and why perceptions differ from reality, and how perceived impacts influence actual results and vice versa. This will provide more insight into the socioeconomic hazards of climate change and aid in the identification of new channels of inequality, which may be caused by disasters or previously unknown inequities.

Furthermore, the potential for effects to spread necessitates modelling studies that link localised studies, provide a robust framework for understanding the socioeconomic risks of climate change. For example, computable general equilibrium models that incorporate estimated results from econometric analysis can aid in analysing how different economic agents and sectors may respond to certain interventions addressing the socioeconomic risks of climate change and extreme weather events, specifically accounting for trade-offs between those most affected and least affected. These approaches will help improve the effectiveness and contribute to the success of future adaptation and mitigation policies.

4.2. Modelling Limitations in Capturing Distributional and Spatial Dynamics

Despite significant advances in the development of CGE models for climate impact analysis, several structural and methodological limitations persist that constrain their ability to fully capture the socioeconomic dimensions of climate change—particularly in relation to inequality, labour productivity, and regional vulnerability.

A key limitation identified in the modelling literature is the scale mismatch between the spatial resolution of CGE models and the fine-grained nature of climate impacts. Most CGE frameworks represent the European Union at the national level or prioritize global coverage, which obscures critical intra-regional heterogeneities in agro-ecological conditions, land endowments, labour markets, and climate exposure. This aggregation limits the capacity of models to simulate spatially explicit mechanisms such as interregional trade adjustments and resource competition—factors that are essential for assessing region-specific vulnerabilities and adaptation pathways.

Complementing these spatial aggregation constraints, CGE models' dependence on the GTAP database poses challenges for sub-national or institutionally detailed analysis. Although GTAP's harmonized global datasets underpin models like ICES, GEM-E3, MIRAGE, and EuroTERM (Capros et al., 2013; Decreux & Valin, 2007; Wittwer, 2022), its legacy sectoral classifications, lacks direct correspondence with contemporary statistical standards, necessitating complex concordance procedures and auxiliary data sources to enable integration with official statistics (Rueda-Cantuche et al., 2020). As demonstrated by Wittwer (2022) in adapting GTAP's national-level data to NUTS-2 regions in the EuroTERM model, this misalignment with NACE Rev. 2 classifications necessitates concordances and auxiliary regional data, adding complexity and uncertainty to CGE database construction and limiting GTAP's suitability for detailed sub-national modelling without extensive post-processing.

While models such as RHOMOLO, EuroTERM, and ICES offer enhanced spatial disaggregation, these capabilities remain the exception rather than the norm. For instance, ICES models only 125 EU-plus-UK regions—just over half of the 242 NUTS-2 units—limiting its ability to portray the full spatial heterogeneity required for rigorous regional climate-impact analysis. RHOMOLO, despite covering all EU NUTS-2 regions, aggregates all non-EU economies into a single "rest-of-the-world" account and collapses agriculture, forestry, and fishing into a single composite sector within a ten-sector schema. This structure, lacking explicit agro-ecological zoning, masks crop- and zone-specific shocks and blurs the transmission of climate-induced disruptions across borders.

Moreover, the direct effects of climate extremes—particularly heat stress—on agricultural labour productivity are frequently omitted or treated as exogenous in most agri-CGE frameworks, despite a growing body of empirical and physiological evidence underscoring their macroeconomic significance (Bartelet et al., 2022; Dasgupta et al., 2021; Roson & Sartori, 2016). In prevailing CGE formulations, labour is typically modelled as a homogeneous production factor with fixed productivity parameters, invariant to climatic conditions. This abstraction overlooks a critical transmission mechanism through which climate change affects agricultural output, household income, and rural welfare. The absence of temperature-sensitive labour productivity functions precludes the endogenous representation of climate-induced reductions in effective labour supply—particularly in outdoor, manual-intensive agricultural systems—thereby leading to a systematic underestimation of total climate damages. This modelling gap is especially consequential in low- and middle-income contexts, where labour intensity is high, mechanisation is limited, and adaptive capacity is constrained.

5. Modelling Framework for Assessing Socioeconomic Risks of Climate Change in Europe

This section presents the integrated modelling framework developed under Task T1.3 of the CROSSEU project. The approach combines econometric analysis with the Subnational-ENGAGE CGE model to estimate the determinants of within-country income inequality using percentile-level income data and macroeconomic indicators, while integrating climate variables to assess the distributional impacts of extreme weather events.

5.1. Econometric Modelling of Income Inequality and Climate Impacts

The econometric analysis in WP1 is structured in two parts: The first part (currently in progress) brings together two global macroeconomic datasets to estimate the key determinants of within-country income inequality. As outlined below, we adopt two complementary approaches: (i) modelling the full income distribution, and (ii) analysing standard inequality indicators such as Gini coefficients. Each approach has distinct strengths and limitations, which will be discussed in detail in the final report. The income distribution modelling (ongoing), briefly presented here, will inform updates to the CGE model's poverty module (ENGAGE). This, in turn, will allow the ENGAGE damage functions to more accurately reflect distributional effects based on historical trends and to project these impacts forward under future CROSSEU scenarios.

The second part of the analysis (scheduled to begin in Month 19) will integrate macroeconomic indicators with climate variables to assess the relationship between income inequality and the frequency and intensity of extreme weather events. The results will be reported in the final deliverable and will serve to validate and complement the global insights generated by the CGE model.

5.2. Subnational CGE Modelling of Climate-Induced Socioeconomic impacts

Complementing the econometric analysis described in Section 6.1, the CGE modelling component of Task T1.3 employs the Subnational-ENGAGE model— a state-of-the-art, regionally disaggregated CGE framework—to simulate the macroeconomic and distributional impacts of climate-induced shocks across European regions. Operating at the NUTS-2 level for the EU27 and the United Kingdom, the model enables a spatially explicit assessment of how climate change affects sectoral outputs, interregional and international trade flows, labour productivity, and income distribution. This high-resolution structure allows for the identification of heterogeneous climate vulnerabilities and the evaluation of policy responses at a subnational scale. The modelling activities are scheduled to conclude by Month 30, delivering key outputs to inform the Decision Support System and policy analysis.

Conventional CGE models, as discussed in Section 3.2, are typically calibrated at the national level and rely on harmonized global databases such as GTAP. While effective for capturing macroeconomic interactions and trade flows, these models are structurally limited in their ability to represent intra-national heterogeneity in climate exposure, adaptive capacity, and socioeconomic vulnerability. Although some contemporary European CGE frameworks—such as RHOMOLO and EuroTERM—have adopted NUTS-2-level spatial disaggregation, they often lack integrated climate-specific modules that account for crop-level biophysical shocks, temperature-sensitive labour productivity, and subnational poverty dynamics.

The Subnational-ENGAGE CGE model is explicitly designed to address the structural and functional limitations that constrain the capacity of conventional CGE frameworks to capture the climate-induced impacts on agriculture. By operating at the NUTS-2 level for the EU27 and the United Kingdom, the model achieves a high degree of spatial disaggregation, enabling the representation of intra-national heterogeneity in agro-ecological conditions, land endowments, labour markets, and production structures. This regional resolution facilitates the identification of spatially differentiated climate vulnerabilities and adaptation responses, which are typically obscured in nationally aggregated or globally oriented CGE models. The model's database is constructed using Eurostat regional accounts, including gross value added and employment statistics, which serve as proxies for allocating national-level economic activity to subnational units. This approach ensures consistency with official statistical classifications and circumvents the sectoral misalignments and concordance challenges associated with GTAP-based models.

The Subnational-ENGAGE includes a detailed representation of the agricultural sector. The model explicitly disaggregates key crop commodities—maize, wheat, rice, and soybean—alongside an aggregated "other crops" category, thereby enabling the simulation of crop-specific responses to climate perturbations. This level of sectoral granularity is critical for capturing heterogeneous yield responses and production adjustments across regions. Furthermore, the model incorporates agro-ecological zoning, allowing for the spatially explicit calibration of productivity shocks based on each crop's biophysical response to temperature and precipitation changes. Climate impacts are introduced as exogenous, crop-specific yield shocks, which are spatially differentiated and calibrated using empirical agro-climatic data, thereby enhancing the model's capacity to simulate region- and crop-specific climate stressors.

The model also addresses a key omission in many existing CGE frameworks: the treatment of climate-induced impacts on labour productivity. While Subnational-ENGAGE does not endogenize the effects of heat stress on agricultural labour through integrated biophysical feedback, it incorporates these impacts exogenously using empirically calibrated damage functions, following the approach of Roson & Sartori (2016). These functions translate temperature increases into reductions in effective labour supply, particularly in outdoor, manual-intensive agricultural systems. Although this approach does not capture dynamic feedback between climate and labour productivity within the model's core structure, it nonetheless allows for the representation of a critical transmission mechanism through which climate change affects agricultural output, household income, and rural welfare. This feature is particularly relevant in regions characterized by high labour intensity and limited mechanization, where climate-induced productivity losses can have significant macroeconomic implications.

In addition to its spatial and sectoral enhancements, Subnational-ENGAGE features a comprehensive treatment of interregional and international trade. The model incorporates bilateral trade flows at the NUTS-2 level, drawing on datasets from the PBL Netherlands Environmental Assessment Agency and recent high-resolution subnational trade networks (Huang & Koutroumpis, 2023). This structure enables the tracking of value-added flows and trade dependencies across regions, facilitating the analysis of how climate shocks propagate through interregional supply chains. For extra-European trade, the model distinguishes between 16 major trading partners and a residual Rest-of-World aggregate, thereby improving the resolution of global economic linkages and feedback mechanisms.

To further enhance its policy relevance, the Subnational-ENGAGE model includes a poverty module that links regional economic outcomes to distributional indicators. Drawing on methodologies such as those implemented in the GlobPov framework (Calzadilla, 2010), the model translates changes in regional income and consumption into poverty metrics—such as headcount ratios and poverty gaps—using internationally harmonized poverty lines. This enables the assessment of how climate-induced shocks and policy responses affect poverty dynamics across NUTS-2 regions, supporting the identification of vulnerable populations and informing the design of equitable adaptation strategies.

Collectively, these innovations position Subnational-ENGAGE as a next-generation CGE framework capable of producing policy-relevant insights into the regional economic impacts of climate change. Its integration of high-resolution spatial data, detailed sectoral disaggregation, biophysical-economic linkages, and trade network modelling addresses the principal limitations of existing models and enables a more robust assessment of climate risks and adaptation strategies at the subnational level.

6. Data Sources

6.1. Econometric Modelling Data

The dataset draws on several authoritative sources. Measures of the dependent variables are taken from the World Bank's Poverty and Inequality Platform (PIP) and the Standardised World Income Inequality Database (SWIID). PIP provides harmonised indicators of poverty and inequality, including poverty headcounts, percentile-level income distributions and shared-prosperity metrics, derived from almost 2,400 household surveys spanning more than 145 countries. The use of percentile data reduces aggregation bias in inequality metrics whilst enabling a better view of tail dynamics. SWIID complements these data by standardising income-inequality series to a common welfare concept and equivalence scale, thereby providing the broadest cross-country and longitudinal coverage currently available.

The use of percentile data reduces aggregation bias in inequality metrics whilst enabling a better view of tail dynamics. Decile-based summaries mask important within-decile disparities, a standard 90/10 ratio ignores the distributional information among the richest and poorest groups, but percentile data can distinguish, say, the top 1% or bottom 1% of the population, allowing analysis of extreme affluence and extreme poverty that would otherwise be averaged out. This is crucial for detecting phenomena like polarisation (e.g. a hollowing-out of the middle class alongside growth at the tails), understanding the concentration of income at the very top, and assessing the depth of poverty at the very bottom. Finally, for both statistical modelling and policy analysis, the higher-resolution PIP data is enormously beneficial. Statistically, it supports more nuanced modelling of the income distribution and the computation of distributional indicators (such as percentile ratios or tail income shares) with less information loss. From a policy perspective, it enables finely targeted and evaluative analysis of redistributive policies: analysts can identify exactly which income percentiles gain or lose under a given intervention and design targeted policies accordingly. SWIID complements these data by standardising income-inequality series to a common welfare concept and equivalence scale, thereby providing the broadest cross-country and longitudinal coverage currently available (Solt 2009, 2020). Its estimates are benchmarked against the Luxembourg Income Study (LIS), whose precision is widely acknowledged, though the LIS covers fewer countries and shorter time periods than SWIID.

Beyond the climate-related explanatory variables of primary interest (in our second specification), we incorporate standard macroeconomic controls sourced from the World Bank's World Development Indicators (WDI).

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6.1.1. Measurement of Income Inequality

In examining the impact of economic performance on income inequality both across and within countries, we adopt two complementary approaches to measuring the dependent variable, with a particular focus on capturing within-country income distribution dynamics.

The first approach involves estimating income distributions at the percentile level by calculating the average income for each percentile. This is achieved by multiplying the income share of each percentile by the country's real GDP (in constant 2017 USD) and dividing the product by the population size of that percentile. The computation is formalised as follows:

$$r\_avg\_wel_{i,p,t} = \frac{Percentile_{i,p,t} * Real\ GDP_{i,t}}{Population_{i,p,t}}$$

where t, p and i denote the percentile $p = 1, \dots, 100$ in country i and year t.

This formulation allows for a granular comparison of income levels across different population segments, facilitating a more nuanced understanding of distributional shifts over time and in response to macroeconomic trends.

To estimate the goodness of fit of income distributions based on macroeconomic indicators (and to analyse the impact of extreme weather events on income inequality), we take the logarithmic values of real average income using their natural logarithms. This transformation enhances the distributional properties of the variable, reducing left skewness and heteroscedasticity, and employing linear estimation assumption, aligning with the log-linear frameworks commonly used in empirical income distribution analysis, denoted as:

$$\ln\_r\_avg\_wel_{i,p,t}$$

The second approach (which is due to start in M21, and it will be discussed in detail in the final report) relies on the Gini index of household disposable income as a summary measure of inequality. This index captures the extent of income disparity after accounting for direct taxes and government transfers but excludes the effects of indirect taxes (such as value-added taxes), public services, and in-kind government transfers. The Gini index ranges from 0 to 100, where a value of 0 denotes perfect equality, where each household receives the same income, and a value of 100 indicates complete inequality, where all income is concentrated in a single household. This measure provides a widely recognised, cross-nationally comparable indicator of overall income inequality, enabling us to complement the percentile-based analysis with a more aggregated, single-value metric.

6.1.2. Measurement of Climate Variables

Climate indicators serve as our primary explanatory variables, with a particular focus on capturing the frequency and intensity of extreme weather events. Unlike prior studies, such as (Baarsch et al., 2020b) and (Paglialunga et al., 2022c), which focus on specific event types (e.g. heatwaves, cold waves, icing days, hot days, and heavy rainfall), our approach diverges by employing a more systematic and standardised set of climate indicators derived from the ERA5 reanalysis dataset. The ERA5 dataset offers high-resolution, annually aggregated, national-level climate data, enabling consistent cross-country comparisons. It provides a novel and harmonised basis for measuring extreme weather events, improving both the accuracy and comparability of our empirical estimates. For each type of weather event, we construct two distinct metrics: one capturing its frequency (i.e., the number of occurrences within a year) and another measuring its intensity (e.g., cumulative deviation from a threshold or severity index). This dual-dimensional approach enables a more comprehensive assessment of how climate extremes impact income distribution dynamics.

We obtained global hourly temperature and precipitation fields at 0.25° resolution for 1961 to 2024 from the fifth-generation ECMWF reanalysis dataset (ERA5; Hersbach et al. (2020)). This dataset provides information from 1940 to the near present and was created by combining vast amounts of historical observations with advanced modelling and data assimilation techniques (Soci et al., 2024). Compared to other global gridded climate sets, ERA5 offers the advantage of covering an extensive period at a relatively high spatial resolution, which was a pre-requisite to match the period of our economic variables, and, in many regions, the set has been found to exhibit less bias (Hassler & Lauer, 2021). ERA5 has also been widely applied in climate change studies, including identifying extreme events (Boettcher et al., 2023; Weynants et al., 2024). Before any analysis, we converted the hourly values to daily average (tmean), minimum (tmin) and maximum (tmax) temperature, and daily total precipitation (pre).

To identify extreme events, we followed the definition of the IPCC, which understands "an extreme weather event as an event that is rare at a particular place and time of year', and an extreme climate event as 'a pattern of extreme weather that persists for some time, such as a season'" (Seneviratne et al., 2021). These events can be loosely grouped into types of Climatic Impact Drivers (CIDs; Ranasinghe et al. (2021)) and we initially focused on events falling into the categories of 'Hot and Cold' or 'Wet and Dry'. Because there exists no single definition on what exactly constitutes an extreme event and because the identification is as Hassler stated with different indices and thresholds (McPhillips et al., 2018), we referred to a collection of climate indices relevant for climate adaptation (Crespi et al., 2020) and the CLIMDEX indices list (https://www.climdex.org/). From those, we selected the following indices that are relevant at the global scale and allow the identification of the severity and frequency of the event: heavy precipitation, heatwaves, cold waves, and icing days (Table 5).

Table 5: Climate indices and their identification conditions

Index	Condition
Hot-days	Daily maximum temperature > 35°C
Heatwave	Excess Heat Factor is positive
Coldwave	Excess Cold Factor is negative
Heavy precipitation	Daily total precipitation > 10mm in agricultural area
Icing days	Daily maximum temperature < 0°C

To capture the effects of extreme heat, we used a selection of three different indicators. First, we selected the relatively simple index of hot days, which is a threshold-based index, identifying any day with a maximum temperature above 35°C. Second, we selected tropical nights to capture nighttime heat stress. A tropical night occurs when the daily minimum temperature remains above 20°C. These nights are significant because they prevent the human body from cooling overnight which leads to permanent heat stress and impacts sleep quality and recovery. Third, we selected the Excess Heat Factor (EHF; Nairn et al., 2014; Nairn & Fawcett, 2013) to account for impacts of extreme temperatures on human health. Compared to other extreme temperature indices, the EHF does not rely on a single temperature threshold but considers the local distribution of historical temperatures. Thus, it accounts for the human body's capability to acclimatise to the conditions it is exposed to and is globally applicable. Often, studies investigating the impacts of heat on human health rely on indices combining temperature with humidity (Andrews et al., 2018; Freychet et al., 2022; Nelson et al., 2024) and thus emphasise immediate human discomfort and heat stress. Here, we focus on the prolonged impact of heatwaves, making the EHF the preferred choice.

Similarly to the indices for extreme heat, we selected three indices to capture different aspects of cold conditions which are likely to have significant impacts on health, agriculture, and infrastructure. The first two of them, frost days and icing days, are threshold-based indices. A frost day occurs when the minimum temperature falls below 0°C, while an icing day occurs when the maximum temperature stays below 0°C. Both of those indices capture events which impact agriculture and transportation, but given the strict thresholds, those conditions will only be met in specific regions, and cold extremes in regions with varying climate are unlikely to be captured. To identify cold extremes in regions that do not experience frost or icing conditions, we added the globally applicable Excess Cold Factor (Nairn & Fawcett, 2013), which accounts for local climatology and the population's adaptation to typical cold conditions[1].

6.1.3. Measurement of Economic Indicators

When analysing income inequality, whether across or within countries, it is important to control for a range of structural and macroeconomic factors that may influence distributional outcomes, and to further examine how economic growth shapes income distribution across population percentiles.

We begin by incorporating sectoral value-added data (in current US dollars) from the World Development Indicators (WDI), capturing economic contributions from the agriculture, industry (including construction), and services sectors. To express these indicators in real terms and account for inflation, we deflate the nominal values using the Consumer Price Index (CPI) (base year 2017). The resulting real values are then transformed using natural logarithms to ensure consistent interpretation in terms of percentage changes and elasticities. These transformed variables are denoted as: ln_real_Agri_GDP, ln_real_Ind_GDP, and ln_real_Serv_GDP. Given that much of the existing literature employs overall GDP rather than disaggregated sectoral values, we also conduct a robustness check by using Principal Component Analysis (PCA).

This method extracts the dominant variance structure from the three sectoral GDP components, yielding a synthetic indicator that captures the common economic trend. This composite variable is denoted as: PC_ln_GDP. This dual approach, disaggregated sectoral analysis alongside a synthesised PCA-based measure, enables a more comprehensive and robust examination of how economic structure and performance interact with income inequality.

The structure of the labour market is a key determinant of income distribution. Elevated unemployment rates can amplify inequality, particularly by limiting income-generating opportunities for lower-skilled or marginalised workers (Shao, 2021). To capture the influence of labour market dynamics on income disparities, we include the unemployment rate as a control variable, denoted as Unemp_rate.

[1] See Technical Appendix 2 for a more detailed description of the calculation and identification process used.

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In addition to labour market conditions, institutional quality plays a pivotal role in shaping income distribution. Strong institutions, characterised by effective legal frameworks, secure property rights, low corruption, and efficient governance, are associated with more equitable income outcomes. Conversely, weak institutional environments often perpetuate inequality. To account for this dimension, we include six widely recognised governance indicators drawn from the World Governance Indicators (WGI): control of corruption, government effectiveness, political stability, rule of law, regulatory quality, and voice and accountability (Dabla-Norris et al., 2015; Jianu et al., 2020). Given the high degree of correlation among these indicators, we apply Principal Component Analysis (PCA) to reduce dimensionality and mitigate multicollinearity. The first principal component, which explains 87.42% of the total variance, is used as a composite index of institutional quality and is denoted as IQ_PC. This approach enables us to account for institutional effects in a parsimonious and statistically robust manner, ensuring that the analysis captures both the structural and institutional determinants of income inequality.

The development of the financial system plays a consequential role in shaping income inequality. Efficient and inclusive financial markets can enhance access to credit and investment opportunities, potentially promoting broader-based economic growth (Fouejieu et al., 2020a). However, when access to financial services is unevenly distributed, such systems may instead reinforce existing disparities.

Demographic characteristics also influence income distribution patterns. Economies with younger, more active workforces may exhibit markedly different distributional dynamics compared to ageing societies (Fouejieu et al., 2020b; Mdingi & Ho, 202). We control for these demographic effects using the population aged 15–64, the working-age population. To address scale differences across countries and facilitate elasticity-based interpretations, we apply a natural logarithmic transformation, resulting in the variable. We deliberately avoid using the age dependency ratio, given its limited temporal variation. However, when access to financial services is unevenly distributed, such systems may instead reinforce existing disparities. To capture this dimension, we include domestic credit to the private sector as a percentage of GDP, denote as DCPS

Gender dynamics in labour force participation are another important determinant of income inequality, reflecting complex interactions between economic opportunity, social norms, and cultural expectations (González & Virdis, 2022; Sobhee, 2020). Female labour force participation (FLFP) is particularly relevant in global inequality research. In certain developing contexts, initial increases in FLFP may exacerbate inequality if the benefits are disproportionately captured by upper-income percentiles (Alfani et al., 2021). To account for this, we include the female labour force participation rate, defined as the percentage of women aged 15 and older participating in the labour force, as reported by the ILO, denoted as Female_rate.

We also account for income polarisation, which captures the degree to which income groups cluster at the extremes, often accompanied by rising social fragmentation. Unlike standard inequality metrics such as the Gini index, polarisation reflects the erosion of the middle class and associated socio-economic tensions (Duro, 2005). To address this dimension, we include a polarisation index, denoted as polarisation, as an additional control variable. Table 6 summarises the names and definitions of the climate variables used in this part of the study, whereas table 7 provides the same information for the economic variables.

Table 6: Climate variable name and definition

Variable Name	Variable Definitions
HW_IF	Standardised NF13 heatwave magnitude interacts with standardised NF13 heatwave number
CW_IF	Standardised NF13 coldwave magnitude interacts with standardised NF13 coldwave number
$Icing\_IF$	Standardised annual area-weighted number of days interacts with the mean affected area (in km^2)
Hot_IF	Standardised annual area-weighted number of days interacts with the mean affected area (in km^2)
$R10mm\_IF$	Standardised number of days with > 10mm rainfall over agricultural land interacts with average total agricultural area exposed to rainfall > 10mm, standardised to the total agricultural area (in km^2)

A country's degree of global economic integration may also influence its income distribution. While trade liberalisation can foster overall growth, its gains are often distributed unequally, with some groups disproportionately affected (Shao, 2021). To capture this aspect, we include a measure of trade openness, calculated as net exports of goods and services as a percentage of GDP. This measure is preferred over gross trade flow indicators as it more directly reflects the economic weight of trade within the domestic economy. It is denoted as $Trade\_Openness$.

By systematically incorporating these controls, spanning financial development, demographic structure, gender dynamics, income polarisation, and trade integration, we are better positioned to isolate the core drivers of income inequality. This comprehensive and methodologically rigorous approach enhances the robustness, validity, and interpretability of our empirical findings, contributing to a more nuanced understanding of income distribution patterns across and within countries.

Table 7: Economic indicators name and definitions

$ln\_real\_Agri\_GDP$	Log-transformed real GDP from the agriculture sector, adjusted for inflation using CPI (2017 base year)
$ln\_real\_Ind\_GDP$	Log-transformed real GDP from the industrial sector, adjusted for inflation using CPI (2017 base year)
$ln\_real\_Serv\_GDP$	Log-transformed real GDP from the services sector, adjusted for inflation using CPI (2017 base year)
$r\_avg\_wel_{i,p,t}$	Real average income for each income percentile, calculated as (percentile share * real GDP) / percentile population
$\ln\_r\_avg\_wel_{i,p,t}$	Log-transformed real average income for each income percentile, calculated as (percentile share * real GDP) / percentile population
$Gini\_index$	Gini index of household disposable income, reflecting inequality after taxes and transfers
$Unemp\_rate$	Unemployment rate as a percentage of the labour force
IQ_PC	Principal Component Analysis (PCA) composite measure of institutional quality
$DCPS$	Domestic credit to the private sector as a percentage of GDP
$ln\_Pop1564$	Log-transformed population aged 15-64
$Female\_rate$	Female labour force participation rate (% of female population aged 15 and above)
$polarisation$	Income polarisation index measuring income group clustering

Trade_Openness	Net exports of goods and services percentage of GDP

6.2. CGE Modelling Data

The Subnational-ENGAGE CGE model is calibrated using a Multi-Regional Social Accounting Matrix (MR-SAM) that builds upon the Eurostat FIGARO intercountry supply-use tables (SUTs). The MR-SAM provides a comprehensive and internally consistent representation of economic flows among institutional agents—households, firms, government, and the rest of the world—both within and across regions. This multi-regional structure enables the explicit modelling of spatial economic interdependencies, such as interregional trade, factor mobility, and income flows. These features are essential for capturing the heterogeneous impacts of climate change and policy interventions across European regions.

6.2.1. Foundational Supply-Use Tables: Eurostat FIGARO

The foundational structure of the MR-SAM is derived from the Eurostat FIGARO intercountry supply-use tables (SUTs). These tables provide harmonised and consistent data on production, intermediate consumption, and final demand across 64 product categories and 45 countries, including the EU's main trading partners and a Rest-of-World (RoW) aggregate. The FIGARO framework ensures coherence between national and regional accounts and supports the disaggregation of both intra-EU and extra-EU trade flows. This is critical for modelling cross-border economic linkages and the propagation of climate-induced shocks through global and regional supply chains. Sectoral and product classifications follow the CPA and NACE Rev.2 standards, ensuring compatibility with other Eurostat datasets and facilitating integration with regional economic data.

6.2.2. Regional Disaggregation of National Accounts

To regionalise the national SUTs, the model employs a suite of Eurostat regional datasets at the NUTS-2 level. These include gross value added (GVA), employment (in hours worked), compensation of employees, household income, and gross fixed capital formation (GFCF), all disaggregated by sector according to the NACE Rev.2 classification. This regional disaggregation ensures consistency with national totals while capturing spatial heterogeneity in economic activity and income distribution. The resulting regional accounts provide the necessary granularity for simulating region-specific economic dynamics and policy impacts.

6.2.3. Interregional Trade Flows

The estimation of interregional trade flows in the Subnational-ENGAGE CGE model draws on recent advances in spatial trade modelling to capture economic interdependencies across European regions. Trade data are sourced from two main datasets. The first, developed by the PBL Netherlands Environmental Assessment Agency (Thissen et al., 2013), provides harmonised NUTS-2-level trade flows for 2000–2010, offering a consistent historical baseline. To improve spatial resolution and reflect more recent dynamics, the model integrates a high-resolution dataset by (García-Rodríguez et al., 2023; Thissen et al., 2013), which estimates bilateral trade flows using firm-level export data, transport infrastructure, and geospatial proximity. This enhances the granularity and accuracy of trade linkages, enabling a more realistic representation of supply chain interdependencies and regional exposure to external shocks. Together, these sources support the construction of a detailed interregional trade matrix capturing both the intensity and direction of trade flows across sectors and regions.

6.2.4. Fiscal and Institutional Accounts

The model includes a comprehensive treatment of fiscal instruments, represented through multiple tax accounts. These include sales taxes (levied on both domestic production and imports), factor use taxes (on labour, capital, and land inputs), production taxes, and factor income taxes. This tax architecture allows for a realistic modelling of public revenue mechanisms and their influence on production costs, consumption behaviour, and income distribution.

To support regional disaggregation, the model integrates data from Eurostat's regional government finance statistics (gov_10a_taxag) and compensation of employees (nama_10r_2lp10), enabling the construction of consistent government and household accounts at the NUTS-2 level. These accounts capture the flow of tax revenues, transfers, and public expenditures across regions and institutional agents.

6.2.5. Agricultural and Sector-Specific Data

Given the agricultural focus of the Subnational-ENGAGE CGE model, particular attention is devoted to the integration and calibration of agricultural production accounts. The model explicitly distinguishes key crop commodities—maize, wheat, rice, and soybean—as separate production activities, alongside an aggregated category for other crops. Agricultural production is modelled at the NUTS-2 regional level, allowing for spatial heterogeneity in crop mix, productivity, and resource endowments. Land is treated as a regionally mobile but sector-specific factor of production. This approach reflects the standard nested production structure in CGE models, where land enters as a primary input alongside labour and capital, and is subject to transformation elasticities that govern its reallocation across uses.

Table 8: Core Datasets Used in MR-SAM Construction.

Dataset Name	Description
Gross Domestic Product (GDP) at current market prices	Measures total economic output by NUTS-2 region, used to benchmark regional economic size.
Gross Value Added (GVA) at basic prices	Sectoral breakdown of output at NUTS-2/3 level, aligned with NACE Rev. 2 classification.
Compensation of Employees	Labour income by region and sector, used to calibrate wage flows and labour market structure.
Household Income	Annual data on primary household income, used to model regional income distribution.
Gross Fixed Capital Formation (GFCF)	Regional investment in fixed assets, informing capital accumulation and sectoral demand.
Economic Accounts for Agriculture	Provides detailed agricultural output, intermediate consumption, and income indicators at regional level.
Main national accounts tax aggregates	Disaggregated tax data by type and country, used to disaggregate tax accounts in the SAM.
Supply and Use Tables (SUTs)	Intercountry SUTs used as the basis for regionalisation and construction of interregional input-output tables.
Interregional Trade Flows	Estimates of bilateral trade between NUTS-2 regions, based on freight movement and business travel data.

7. Methodological Framework

7.1. Econometric Modelling of Income Inequality and Climate Impacts

7.1.1. Income Inequality Distribution Estimation

Our approach begins with a log-linearised regression model that links key macroeconomic indicators to the shape of the income distribution. This method builds on evidence that a country's economic structure and performance are systematically related to how income is distributed across its population. Empirical studies dating back to Kuznets have confirmed, for example, that income inequality is generally lower in the agricultural sector than in the non-agricultural sectors of both developing and developed countries. Campano & Salvatore (2006) leverage these insights by integrating income distribution models with long-term macroeconomic frameworks based on potential output, finding stable relationships between income shares and sectoral GDP over extended horizons. Guided by this theoretical foundation, we formulate a regression-based model to "fit" the entire income distribution as a function of macroeconomic fundamentals and then feed those fitted results into a CGE model to analyse distributional outcomes.

In the first stage, we estimate how a set of carefully chosen macroeconomic variables influence the income distribution. The dependent variables are derived from the income levels at each percentile (1st through 100th) of the distribution, allowing us to model the distribution in fine detail rather than only summary indices. For each country-year in our dataset, the income at each percentile serves as an observation to be explained by contemporaneous macroeconomic indicators. We estimate a fixed-effects panel regression model for the income at each percentile. In essence, for each percentile p (1 to 100), we posit a linear relationship:

$$\ln\_r\_avg\_wel_{i,p,t} = \alpha^p + \beta_1^p \, ln\_real\_GDP_{i,t}^s + \boldsymbol{\beta_2^p X_{i,t}} + \gamma_i^p + \theta_t^p + \epsilon_{it}^p \qquad (1)$$

where $\ln\_r\_avg\_wel_{i,q,t}$ denotes our measure of income inequality in country i and year t, represented as the logarithm of the average income of percentile p. The term $\ln\_real\_sectorGDP_{i,t}^s$ captures three sector-specific specifications of real GDP, where s refers to $\mathrm{ln\_real\_Agri\_GDP}_{i,t}$, $\mathrm{ln\_real\_Ind\_GDP}_{i,t}$, or $\mathrm{ln\_real\_Serv\_GDP}_{i,t}$. The vector $\boldsymbol{X_{i,t}}$ comprises key determinants of income distribution identified in the literature, encompassing socio-economic, technological, institutional, and global drivers of inequality, as detailed in Section "Data – Measurement of Economic Indicators". γ_i^p and θ_t^p represent country and time fixed effects, respectively; ϵ_{it}^p is the error term; and α^p denotes intercept specific to that percentile's equation, capturing unobserved country-specific factors that consistently influence the distribution.

By using country fixed effects, we control for all time-invariant differences across countries, focusing the estimation on within-country variations over time. This approach improves identification of the impact of the macro variables: for example, if one country's distribution is generally more unequal due to some fixed national characteristic, that effect is differenced out, allowing the coefficients β to reflect the influence of changes in the macro indicators on the distribution. We estimate the above regression separately for each percentile, yielding a set of coefficient estimates that vary by percentile. This effectively produces a regression-based fitted income distribution for each country-year – i.e. the collection of predicted percentile incomes from $p1$ to $p100$. Importantly, the model is linear in log-income, so it captures marginal effects of each macro indicator on the (log) income at a given percentile. The linear specification proved adequate in our case, and the high goodness-of-fit for many percentile equations suggests a stable linear relationship.

7.1.2. Generating Fitted Values and Transformation

Once the final fixed-effects specifications are estimated, we use them to generate fitted income values for each percentile. Because we performed the regression in logarithmic terms ($ln\_r\_avg\_wel_{i,p,t}$), we transform the results back to level incomes. For each percentile and each country-year, we take the predicted $ln\_r\_avg\_wel_{i,p,t}$ from the regression and exponentiate it to obtain the predicted income level $ln\_r\_\widehat{avg\_wel}_{\iota,p,t}$. This exponentiation yields the modelled income at that percentile, in the original units of currency. However, a well-known issue arises when converting log-linear predictions to levels: the logarithmic prediction is a geometric mean (or median) predictor, which can under-estimate the arithmetic means of income due to Jensen's inequality. To correct for this, we apply an RMSE-based adjustment. Specifically, let σ_p be the standard error of the regression (the Root Mean Squared Error) for percentile p. We adjust the exponentiated value by a factor of $exp\left(\frac{1}{2}\sigma_p^2\right)$, which is a standard smearing estimate to obtain an unbiased predictor of the mean on the original scale. In practice, this means the fitted value is calculated as:

$$r\_\widehat{avg\_wel}_{\iota,p,t} = \exp\left(ln\_r\_\widehat{avg\_wel}_{\iota,p,t}\right) + \exp\left(\frac{1}{2}var(\epsilon_{i,p,t})\right) \quad (2)$$

where $ln\_r\_\widehat{avg\_wel}_{\iota,p,t}$ is the predicted log-income and $var(\epsilon_{i,p,t})$ is the variance of the regression residual (with σ_p^2 representing an estimate of that variance). This RMSE adjustment ensures that the sum or mean of our predicted income aligns more closely with actual income totals, and that the fitted distribution inequality measures are not systematically biased low. After this adjustment, we obtain the final fitted income distribution for each country-year, essentially a set of 100 income values (one per percentile) that are predicted by our model.

7.1.3. Climate Risk Modelling

Building on Equation (1), we extend the model by incorporating variables that capture extreme climate events. Accordingly, we specify a set of models in which the logarithmic growth of income at each percentile is regressed on the climate event variables in $\boldsymbol{CR}_{i,t}$, along with the relevant macroeconomic and institutional covariates. This approach allows for a granular examination of how climate extremes differentially affect income dynamics across the distribution, thereby enriching our understanding of the mechanisms linking environmental shocks to inequality.

$$ln\_r\_avg\_wel_{i,p,t} = \alpha^p + \boldsymbol{\beta_1 CR_{i,t}} + \beta_2^p \, ln\_real\_GDP_{i,t}^s + \boldsymbol{\beta_3^p X_{i,t}} + \gamma_i^p + \theta_t^p + \epsilon_{it}^p \quad (3)$$

where $\boldsymbol{CR}_{i,t}$ is a vector of extreme climate events, including HW_IF, CW_IF, $Icing\_IF$, Hot_IF, and $R10mm\_IF$ in country i and year t. This extended methodological framework enables us to identify and quantify the contribution of climate extremes to income inequality. It also allows us to evaluate both the direct impact of climate shocks and their interaction with economic growth, particularly how such events mediate or amplify income growth across percentiles under evolving climatic conditions.

Earlier sections have outlined potential sources of heterogeneity in climate change responses, such as national vulnerability and resilience metrics, which may mediate economic adaptation to climatic shocks. Importantly, our analysis shifts focus from aggregate GDP to sectoral GDPs, reflecting the crucial transmission mechanisms through which climate change impacts inequality. The rationale for this shift lies in the fact that income percentiles are often unevenly connected to different sectors, rendering them variably exposed to sector-specific economic dynamics.

In the third specification, the estimation approach is adjusted by employing the Gini coefficient as the measure of income inequality. Given the characteristics of the Gini coefficient as the dependent variable, we adopt a panel linear regression framework, while maintaining all other modelling settings consistent with the previous specifications.

7.1.4. Preliminary Results

To provide a glimpse of the performance of our current models and the goodness of fit we have achieved so far, we present in the Technical Appendix 3 visualisations of some of our estimated Kernel density functions showing the fitted values from our model to the actual real average welfare levels. These comparisons illustrate the predictive performance of our specification and provide preliminary validation for its use in subsequent climate-inequality modelling.

7.2. Subnational CGE Modelling of Climate-Induced Socioeconomic Impacts

7.2.1. Construction of the Agri-Focused Multi-Regional SAM

The multi-regional SAM was built in a two-stage process that links Eurostat's national supply–use information with region-specific accounts and sectoral detail relevant for CGE analysis. The national benchmark relied on Eurostat's FIGARO supply-use tables (SUTs), which provide matrices by product and industry, detailing how domestic production and imports are allocated across intermediate consumption and final demand categories. From these national SUTs, a balanced national SAM was constructed, integrating production, income generation, and institutional expenditure in a consistent accounting framework.

Tax and transfer flows were disaggregated using Eurostat's main aggregates for government revenue to enhance the fiscal resolution of the SAM. This disaggregation yielded a detailed representation of five key tax categories: (i) import duties, (ii) sales taxes on imported goods and services, (iii) sales taxes on domestically produced goods and services, (iv) taxes on factors of production, and (v) other production taxes.

The national SUT is converted into a multi-regional Social Accounting Matrix by mapping every national transaction X_k (for product or factor k) to the NUTS-2 level. Whenever Eurostat publishes a complete regional series—e.g. compensation of employees, regional employment, household disposable income or gross fixed capital formation (GFCF)—the corresponding variable is used directly as the regional key. Where official NUTS-2 breakdowns are absent, an indicator-ratio procedure is applied: each missing cell is distributed across regions in proportion to a proxy indicator I_k (for example, regional gross value added or employment, chosen according to the nature of the account), with the proportional allocations calibrated so that their sum exactly reproduces the original national aggregate. The regional allocation for account i in region r can be expressed as:

$$X_{r,k} = \frac{I_{r,k}}{\sum_r I_{r,k}} X_k$$

where X_r is the national aggregate for account i, $I_{r,k}$ is the proxy indicator for region r, and the denominator sums that indicator across all regions r.

Interregional trade flows were estimated using the origin–destination matrices provided by (García-Rodríguez et al., 2023; Thissen et al., 2013), which align with FIGARO sectoral definitions. For each product, regional exports were scaled to equal national supply minus regional absorption, and regional imports to fill the gap between regional demand and local production. The result is a balanced interregional trade matrix—

commodity-by-commodity and region-by-region—which is indispensable for counterfactual CGE simulations.

Finally, an agri-focused SAM was developed by disaggregating the aggregate crop sector into five distinct activities—maize, wheat, rice, soybean, and other crops—at the NUTS-2 level, based on Eurostat's Economic Accounts for Agriculture. Land was introduced as a separate production factor: total regional agricultural land endowments were sourced from FAO's Global Agro-Ecological Zones (GAEZ) database and allocated across the five crop activities in proportion to harvested-area shares.

Once the regional and agri-focused accounts have been established through the above steps, the entire multi-regional SAM underwent a balancing routine. A cross-entropy variant of the RAS algorithm was then applied to adjust the interior cells so that, for every institution, activity, and commodity, row totals exactly matched the corresponding column totals while minimising deviations from the preliminary estimates. Convergence was declared once the maximum proportional adjustment in any cell fell below 10^{-6}, thus ensuring full numerical consistency without materially altering the underlying technological or regional distributions.

7.2.2. Formulation of Policy and Shock Scenarios – Heat Stress on Labour productivity

The scenario design centres on an exogenous heat-stress shock that propagates through the agricultural system via empirically calibrated damage functions. The reference (baseline) path keeps all climatological variables at their historical averages for the benchmark year; two counter-factual scenarios then impose regional temperature increments corresponding to mid-century global mean anomalies under the SSP2-4.5 ($\Delta T \simeq +2$ °C) and SSP5-8.5 ($\Delta T \simeq +2.4$ °C) pathways. For each NUTS-2 region, gridded daily near - surface air temperature (tas) and relative humidity (rh) data were obtained from the ISIMIP3b dataset, spatially aggregated to the regional level, and used to calculate the mean temperature anomalies corresponding to the SSP2-4.5 and SSP5-8.5 scenarios.

Regional temperature and humidity series were next transformed into a monthly Wet-Bulb-Globe Temperature (WBGT) indicator using the standard meteorological approximation (refer to Lemke & Kjellstrom (2012) and Roson & Sartori (2016) for more information on WBGT calculations).

$$WBGT = 0.567T + 3.94 + 0.393E$$

Where, E denotes water-vapour pressure derived from relative humidity. The monthly WBGT values were mapped onto sector-specific work-ability curves that relate thermal stress to the share of an hour that can be spent productively. For agricultural activities the curve is defined by a zero-impact threshold at 26°C and a lower bound of 25 % productivity reached at 36°C. By integrating these curves over the monthly distribution of WBGT, an annual percentage change in effective labour productivity is obtained for each region and warming level.

These percentage losses are implemented in the CGE model as Hicks-neutral reductions to the agricultural labour endowment, leaving factor remuneration endogenous but preserving the initial technical coefficients. In combination with the temperature-driven yield shocks described below, the labour-productivity damage functions ensure that the simulated agricultural supply response fully internalises both biophysical and human-capital dimensions of heat stress.

7.2.3. Formulation of Policy and Shock Scenarios – Crop Yield shocks

To assess the potential impacts of climate change on agricultural productivity we are going to use the GAEZ v5 dataset, which incorporates the most recent climate data and modelling techniques. This enables more accurate and regionally detailed assessments of how climate change will influence crop performance.

By using the GAEZ dataset, we are going to account for future climate variability, as GAEZ includes projections based on multiple Global Circulation Models (GCMs), Global Crop Models, and Shared Socioeconomic Pathways (SSPs). These scenarios reflect a range of possible futures, from low-emission pathways with strong mitigation efforts to high-emission trajectories with limited climate action. The use multiple GCMs and crop models generates a range of yield estimates rather than a single deterministic outcome. This ensemble approach helps quantify the uncertainty associated with climate projections and model assumptions, offering a more robust basis for decision-making. A special attention will be given to the SSP2-4.5 and SSP5-8.5 scenarios.

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8. Conclusion

This interim report presents a comprehensive literature review and the development of methods and models to assess the socio-economic impacts of mitigation and adaptation strategies to cope with climate change at the European level. It combines a systematic literature review with a dual-modelling framework that merges empirical econometric analysis and a regionally disaggregated Computable General Equilibrium (CGE) model. The econometric component estimates the distributional impacts of climate and macroeconomic variables on income inequality using percentile-level data, while the CGE model—Subnational-ENGAGE—simulates the propagation of climate-induced shocks across sectors and regions at the NUTS-2 level. Together, these approaches enhance the analytical capacity to capture both observed and simulated distributional consequences of extreme weather events, offering a robust foundation for assessing regional vulnerabilities and informing equitable adaptation strategies.

The literature review conducted in Section 2 aimed to systematically assess the socioeconomic risks of climate change, with a particular focus on extreme weather events and studies specific to the European context. The review explored how climate change exacerbates existing inequities—particularly those related to income, gender, and geographic vulnerability—by synthesising findings from 78 peer-reviewed studies. It examined the methodologies, datasets, and empirical strategies employed across the literature to identify both common findings and critical gaps. While developing countries have historically been more vulnerable to climate change, the review highlights a growing concern within industrialised regions such as Europe, where the socioeconomic consequences of climate-induced shocks are becoming increasingly evident.

The findings underscore that extreme weather events pose significant and uneven risks across Europe, disproportionately affecting low-income households, marginalised neighbourhoods, labour-intensive sectors, and vulnerable demographic groups such as women and the elderly. These impacts are shaped by a complex interplay of socioeconomic factors, including pre-existing inequality, infrastructure quality, and institutional capacity. The review also reveals that no single methodological approach can fully capture the multifaceted nature of these risks. In response, the CROSSEU project adopts a micro-level, regionally disaggregated perspective to assess how different types of extreme weather events influence inequality across European regions. While the literature provides valuable insights into the transmission channels of climate risk, it offers limited guidance on how to manage these risks effectively. Therefore, this deliverable not only synthesises existing knowledge but also lays the groundwork for policy-relevant modelling that can inform targeted adaptation and mitigation strategies, as further developed in Section 4.3 and throughout the modelling framework.

In advancing the understanding of climate-induced socioeconomic risks, this report introduces a novel and methodologically rigorous modelling framework that integrates empirical econometric analysis with a spatially disaggregated CGE model at the NUTS-2 level. This dual approach enables the simulation of both observed and projected impacts of climate change on income distribution, sectoral performance, and regional economies. The econometric component leverages percentile-level income data—derived from harmonised global datasets such as PIP and SWIID—to estimate how macroeconomic structures and climate variables influence income inequality across and within countries. This high-resolution modelling captures the full income distribution, allowing for a nuanced understanding of how different income percentiles are affected by economic and environmental shocks.

The CGE component uses a subnational disaggregated version of the ENGAGE model to assess climate impacts on agriculture and labour productivity across 241 NUTS-2 regions in the EU27 and UK. Built on Eurostat's FIGARO data and regional trade flows, the model captures interregional economic linkages and sectoral dynamics. It simulates how climate shocks propagate through supply chains, affecting production, trade, and welfare. The model places particular emphasis on agriculture, with explicit representation of key crop commodities (maize, wheat, rice, soybean) and detailed coverage of manufacturing, energy, extraction, services, and public sectors. It also includes a comprehensive fiscal architecture, modelling multiple tax instruments and their effects on production, consumption, and income distribution.

To assess distributional outcomes, the ENGAGE model is linked to the GLOBPOV poverty module, enabling the estimation of key inequality and poverty indicators—including the Gini index, poverty headcount, poverty gap, and squared poverty gap—under various climate and policy scenarios. Simulations are conducted across harmonised climate-socioeconomic pathways, combining RCPs and SSPs, specifically from high-emission scenarios (e.g. SSP5-RCP8.5) to more moderate mitigation pathways (e.g. SSP2-RCP4.5). This scenario-based framework supports robust analysis of the distributional effects of climate change and the equity implications of mitigation and adaptation strategies across European regions.

This interim deliverable presents progresses achieved in the task T1.3. The work completed to date has been methodology and model development (econometric and CGE). The assessment of the distributional effects of climate change and analyse of the implication of mitigation and adaptation strategies on European poverty and inequality will be reported in the final version of the deliverable D1.3 due Month 30.

9. References

Aakre, S., & Rübbelke, D. T. G. (2010). Adaptation to climate change in the European union: efficiency versus equity considerations. *Environmental Policy and Governance*, *20*(3), 159–179. https://doi.org/10.1002/EET.538https://doi.org/10.2478/sbe-2020-0055

Alam, M. M., Taufique, K. M. R., & Sayal, A. (2017). Do climate changes lead to income inequality? Empirical study on the farming community in Malaysia. *International Journal of Environment and Sustainable Development*, *16*(1), 43–59. https://doi.org/10.1504/IJESD.2017.080848

Albu Ada-Cristina , & Albu Lucian-Liviu (2020). The impact of climate change on income inequality. Evidence from European Union Countries. *Studies in Business and Economics*, *15*(3), 223–235.; https://doi.org/10.2478/sbe-2020-0055

Alfani, F., Clementi, F., Fabiani, M., Molini, V., & Valentini, E. (2021). Does Gender Equality in Labor Participation Bring Real Equality? Evidence From Developed and Developing Countries. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3835861

Andrews, O., Le Quéré, C., Kjellstrom, T., Lemke, B., & Haines, A. (2018). Implications for workability and survivability in populations exposed to extreme heat under climate change: a modelling study. *The Lancet Planetary Health*, *2*(12), e540–e547. https://doi.org/10.1016/S2542-5196(18)30240-7

Ashenafi, B. B. (2022). Greenhouse gas emission widens income inequality in Africa. *Environmental Science and Pollution Research*, *29*(31), 46691–46707. https://doi.org/10.1007/S11356-022-18925-5/FIGURES/1

Baarsch, F., Granadillos, J. R., Hare, W., Knaus, M., Krapp, M., Schaeffer, M., & Lotze-Campen, H. (2020a). The impact of climate change on incomes and convergence in Africa. *World Development*, *126*, 104699. https://doi.org/10.1016/J.WORLDDEV.2019.104699

Baarsch, F., Granadillos, J. R., Hare, W., Knaus, M., Krapp, M., Schaeffer, M., & Lotze-Campen, H. (2020b). The impact of climate change on incomes and convergence in Africa. *World Development*, *126*, 104699. https://doi.org/10.1016/J.WORLDDEV.2019.104699

Belasen, A. R., & Polachek, S. W. (2009). How Disasters Affect Local Labor Markets. *Journal of Human Resources*, *44*(1), 251–276. https://doi.org/10.3368/JHR.44.1.251

Berlemann, M., & Wenzel, D. (2018). Hurricanes, economic growth and transmission channels: Empirical evidence for countries on differing levels of development. *World Development*, *105*, 231–247. https://doi.org/10.1016/J.WORLDDEV.2017.12.020

Funded by the European Union

Boettcher, M., Röthlisberger, M., Attinger, R., Rieder, J., & Wernli, H. (2023). The ERA5 Extreme Seasons Explorer as a Basis for Research at the Weather and Climate Interface. *Bulletin of the American Meteorological Society*, *104*(3), E631–E644. https://doi.org/10.1175/BAMS-D-21-0348.1

Bosello, F., Nicholls, R. J., Richards, J., Roson, R., & Tol, R. S. J. (2012). Economic impacts of climate change in Europe: Sea-level rise. *Climatic Change*, *112*(1), 63–81. https://doi.org/10.1007/S10584-011-0340-1/TABLES/8

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: Evidence from Vietnam. *Applied Economics*, *46*(15), 1751–1766. https://doi.org/10.1080/00036846.2014.884706;WGROUP:STRING:PUBLICATION

Calzadilla, A., Rehdanz, K., & Tol, R. S. J. (2011). Water scarcity and the impact of improved irrigation management: a computable general equilibrium analysis. *Agricultural Economics*, *42*(3), 305–323.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. S. J., & Ringler, C. (2014). Climate change and agriculture: Impacts and adaptation options in South Africa. *Water Resources and Economics*, *5*, 24–48. https://doi.org/10.1016/J.WRE.2014.03.001

Campano, F., & Salvatore, D. (2006). Income Distribution: Includes CD. *Income Distribution: Includes CD*, 1–222. https://doi.org/10.1093/0195300912.001.0001

Capetillo-Ordaz, N. B., Martín-Consuegra, F., Alonso, C., Terés-Zubiaga, J., & Koutra, S. (2024). Inclusivity in urban energy transitions: A methodological approach for mapping gendered energy vulnerability. *Energy Research & Social Science*, *109*, 103426. https://doi.org/10.1016/J.ERSS.2024.103426

Cappelli, F., Costantini, V., & Consoli, D. (2021a). The trap of climate change-induced "natural" disasters and inequality. *Global Environmental Change*, *70*, 102329.

Cappelli, F., Costantini, V., & Consoli, D. (2021b). The trap of climate change-induced "natural" disasters and inequality. *Global Environmental Change*, *70*, 102329.

Cardil, A., Molina, D. M., & Kobziar, L. N. (2014). Extreme temperature days and their potential impacts on southern Europe. *Natural Hazards and Earth System Sciences*, *14*(11), 3005–3014.

Cevik, S., & Jalles, J. T. (2023a). For whom the bell tolls: Climate change and income inequality. *Energy Policy*, *174*, 113475. https://doi.org/10.1016/J.ENPOL.2023.113475

Cevik, S., & Jalles, J. T. (2023b). For whom the bell tolls: Climate change and income inequality. *Energy Policy*, *174*, 113475.

Crespi, A., Terzi, S., Cocuccioni, S., Zebisch, M., Berckmans, J., & Füssel, H. (2020). *Climate-related hazard indices for Europe*.

https://doi.org/10.25424/CMCC/CLIMATE_RELATED_HAZARD_INDICES_EUROPE_2020

Dabla-Norris, Era., Kochhar, Kalpana., Suphaphiphat, Nujin., Ricka, Frantisek., & Trounta, Evridiki. (2015). *Causes and consequences of income inequality : a global perspective*. 39.

Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(20), 9808–9813. https://doi.org/10.1073/PNAS.1816020116/SUPPL_FILE/PNAS.1816020116.SAPP.PDF

D'Ippoliti, D., Michelozzi, P., Marino, C., De'Donato, F., Menne, B., Katsouyanni, K., Kirchmayer, U., Analitis, A., Medina-Ramón, M., Paldy, A., Atkinson, R., Kovats, S., Bisanti, L., Schneider, A., Lefranc, A., Iñiguez, C., & Perucci, C. A. (2010). The impact of heat waves on mortality in 9 European cities: Results from the EuroHEAT project. *Environmental Health: A Global Access Science Source*, *9*(1), 1–9. https://doi.org/10.1186/1476-069X-9-37/FIGURES/2

Dissanayake, S., Mahadevan, R., & Asafu-Adjaye, J. (2019). Is there a role for trade liberalization in mitigating the impacts of climate change on agriculture? *Economic Analysis and Policy*, *62*, 307–324. https://doi.org/10.1016/J.EAP.2019.04.006

Ellena, M., Ballester, J., Mercogliano, P., Ferracin, E., Barbato, G., Costa, G., & Ingole, V. (2020a). Social inequalities in heat-attributable mortality in the city of Turin, northwest of Italy: a time series analysis from 1982 to 2018. *Environmental Health: A Global Access Science Source*, *19*(1), 1–14. https://doi.org/10.1186/S12940-020-00667-X/TABLES/2

Fouejieu, A., Sahay, R., Cihak, M., & Chen, S. (2020). Financial inclusion and inequality: A cross-country analysis. *Journal of International Trade and Economic Development*, *2020*(8), 1018–1048. https://doi.org/10.1080/09638199.2020.1785532;WEBSITE:WEBSITE:TFOPB;PAGEGROUP:STRING:PUBLICATION

Freychet, N., Hegerl, G. C., Lord, N. S., Lo, Y. T. E., Mitchell, D., & Collins, M. (2022). Robust increase in population exposure to heat stress with increasing global warming. *Environmental Research Letters*, *17*(6), 064049. https://doi.org/10.1088/1748-9326/AC71B9

Ganzleben, C., & Kazmierczak, A. (2020). Leaving no one behind - Understanding environmental inequality in Europe. *Environmental Health: A Global Access Science Source*, *19*(1), 1–7. https://doi.org/10.1186/S12940-020-00600-2/PEER-REVIEW

García-Rodríguez, A., Lazarou, N., Mandras, G., Salotti, S., Thissen, M., & Kalvelagen, E. (2023). *A NUTS-2 European Union interregional system of Social Accounting Matrices for the year 2017: The RHOMOLO V4 dataset*. https://www.econstor.eu/handle/10419/283086

Funded by the European Union

Gómez-Acebo, I., Llorca, J., Rodríguez-Cundín, P., & Dierssen-Sotos, T. (2012). Extreme temperatures and mortality in the North of Spain. *International Journal of Public Health*, *57*, 305–313.

González, F. A. I., & Virdis, J. M. (2022). Global development and female labour force participation: evidence from a multidimensional perspective. *Journal of Gender Studies*, *31*(3), 289–305. https://doi.org/10.1080/09589236.2021.1949581;JOURNAL:JOURNAL:CJGS20;WGROUP:STRING:PUBLICATION

Guliyev, H. (2023). Associations of (un)observed factors and gender inequality in European countries: Evidence from spatial panel data model. *Applied Geography*, *159*, 103066. https://doi.org/10.1016/J.APGEOG.2023.103066

Hasegawa, T., Fujimori, S., Havlík, P., Valin, H., Bodirsky, B. L., Doelman, J. C., Fellmann, T., Kyle, P., Koopman, J. F. L., Lotze-Campen, H., Mason-D'Croz, D., Ochi, Y., Pérez Domínguez, I., Stehfest, E., Sulser, T. B., Tabeau, A., Takahashi, K., Takakura, J., van Meijl, H., … Witzke, P. (2018). Risk of increased food insecurity under stringent global climate change mitigation policy. *Nature Climate Change 2018 8:8*, *8*(8), 699–703. https://doi.org/10.1038/s41558-018-0230-x

Hassler, B., & Lauer, A. (2021). Comparison of Reanalysis and Observational Precipitation Datasets Including ERA5 and WFDE5. *Atmosphere 2021, Vol. 12, Page 1462*, *12*(11), 1462. https://doi.org/10.3390/ATMOS12111462

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., … Thépaut, J. N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/QJ.3803

Huynh, C. M., & Hoang, H. H. (2024). Climate change and income inequality in Asia: how does institutional quality matter? *Journal of the Asia Pacific Economy*, 1–25.

Inés, G. A., Llorca, J., Paz, R. C., & Trinidad, D. S. (2012). Extreme temperatures and mortality in the North of Spain. *International Journal of Public Health*, *57*(2), 305–313. https://doi.org/10.1007/S00038-010-0229-1/TABLES/6

Issoufou-Ahmed, O., & Sebri, M. (2024). On the transmission channels driving climate change-income inequality nexus in sub-Saharan African countries. *Business Strategy and Development*, *7*(1), e339. https://doi.org/10.1002/BSD2.339;PAGEGROUP:STRING:PUBLICATION

Janssens, C., Havlík, P., Krisztin, T., Baker, J., Frank, S., Hasegawa, T., Leclère, D., Ohrel, S., Ragnauth, S., Schmid, E., Valin, H., Van Lipzig, N., & Maertens, M. (2020). Global hunger and climate change adaptation through international trade. *Nature Climate Change 2020 10:9*, *10*(9), 829–835. https://doi.org/10.1038/s41558-020-0847-4

Jianu, I., Dobre, I., Bodislav, D. A., Radulescu, C. V., & Burlacu, S. (2020). *The implications of institutional specificities on the income inequalities drivers in European Union*. *53*(2). https://doi.org/10.24818/18423264/53.2.19.04

Jorgenson, A. K., Schor, J. B., Huang, X., & Fitzgerald, J. (2015). Income inequality and residential carbon emissions in the United States: A preliminary analysis. *Human Ecology Review*, *22*(1), 93–106.

Juliá, R., & Duchin, F. (2007). World trade as the adjustment mechanism of agriculture to climate change. *Climatic Change*, *82*(3–4), 393–409. https://doi.org/10.1007/S10584-006-9181-8/METRICS

Kellenberg, D. K., & Mobarak, A. M. (2008). Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics*, *63*(3), 788–802. https://doi.org/10.1016/J.JUE.2007.05.003

Koks, E. E., Thissen, M., Alfieri, L., De Moel, H., Feyen, L., Jongman, B., & Aerts, J. (2019). The macroeconomic impacts of future river flooding in Europe. *Environmental Research Letters*, *14*(8), 084042.

Leiter, A. M., Oberhofer, H., & Raschky, P. A. (2009). Creative disasters? Flooding effects on capital, labour and productivity within European firms. *Environmental and Resource Economics*, *43*(3), 333–350. https://doi.org/10.1007/S10640-009-9273-9/METRICS

Lynham, J., Noy, I., & Page, J. (2017). The 1960 Tsunami in Hawaii: Long-Term Consequences of a Coastal Disaster. *World Development*, *94*, 106–118. https://doi.org/10.1016/J.WORLDDEV.2016.12.043

Marí-Dell'Olmo, M., Tobías, A., Gómez-Gutiérrez, A., Rodríguez-Sanz, M., García de Olalla, P., Camprubí, E., Gasparrini, A., & Borrell, C. (2019a). Social inequalities in the association between temperature and mortality in a South European context. *International Journal of Public Health*, *64*(1), 27–37. https://doi.org/10.1007/S00038-018-1094-6/TABLES/2

Marí-Dell'Olmo, M., Tobías, A., Gómez-Gutiérrez, A., Rodríguez-Sanz, M., García de Olalla, P., Camprubí, E., Gasparrini, A., & Borrell, C. (2019b). Social inequalities in the association between temperature and mortality in a South European context. *International Journal of Public Health*, *64*, 27–37.

Mateos, R. M., Sarro, R., Díez-Herrero, A., Reyes-Carmona, C., López-Vinielles, J., Ezquerro, P., Martínez-Corbella, M., Bru, G., Luque, J. A., & Barra, A. (2023). Assessment of the socio-economic impacts of extreme weather events on the coast of southwest Europe during the period 2009–2020. *Applied Sciences*, *13*(4), 2640.

McPhillips, L. E., Chang, H., Chester, M. V., Depietri, Y., Friedman, E., Grimm, N. B., Kominoski, J. S., McPhearson, T., Méndez-Lázaro, P., Rosi, E. J., & Shafiei Shiva, J. (2018). Defining Extreme Events: A Cross-Disciplinary Review. *Earth's Future*, *6*(3), 441–455. https://doi.org/10.1002/2017EF000686;SUBPAGE:STRING:FULL

Mdingi, K., & Ho, S. Y. (2021). Literature review on income inequality and economic growth. *MethodsX*, *8*, 101402. https://doi.org/10.1016/J.MEX.2021.101402

Mideksa, T. K. (2010). Economic and distributional impacts of climate change: The case of Ethiopia. *Global Environmental Change*, *20*(2), 278–286. https://doi.org/10.1016/J.GLOENVCHA.2009.11.007

Moore, F. C., Baldos, U., Hertel, T., & Diaz, D. (2017). New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications 2017 8:1*, *8*(1), 1–9. https://doi.org/10.1038/s41467-017-01792-x

Nairn, J. R., & Fawcett, R. G. (2013). *Defining heatwaves: heatwave defined as a heat-impact event servicing all community and business sectors in Australia*. Centre for Australian Weather and Climate Research.

Nairn, J. R., Fawcett, R. J. B., Ebi, K. L., & Hess, J. (2014). The Excess Heat Factor: A Metric for Heatwave Intensity and Its Use in Classifying Heatwave Severity. *International Journal of Environmental Research and Public Health 2015, Vol. 12, Pages 227-253*, *12*(1), 227–253. https://doi.org/10.3390/IJERPH120100227

Navas-Martín, M., López-Bueno, J. A., Ascaso-Sánchez, M. S., Sarmiento-Suárez, R., Follos, F., Vellón, J. M., Mirón, I. J., Luna, M. Y., Sánchez-Martínez, G., Culqui, D., Linares, C., & Díaz, J. (2022). Gender differences in adaptation to heat in Spain (1983–2018). *Environmental Research*, *215*, 113986. https://doi.org/10.1016/J.ENVRES.2022.113986

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason D'Croz, D., Van Meijl, H., Van Der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., … Willenbockel, D. (2014). Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3274–3279. https://doi.org/10.1073/PNAS.1222465110/SUPPL_FILE/SD03.TXT

Nelson, G. C., Vanos, J., Havenith, G., Jay, O., Ebi, K. L., & Hijmans, R. J. (2024). Global reductions in manual agricultural work capacity due to climate change. *Global Change Biology*, *30*(1), e17142. https://doi.org/10.1111/GCB.17142;CTYPE:STRING:JOURNAL

Neumayer, E., & Plümper, T. (2007). The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy, 1981–2002. *Annals of the Association of American Geographers*, *97*(3), 551–566.

Nguyen, C. P., & Nguyen, B. Q. (2023). From natural risk to social justice: The influence of natural threats on gender inequality. *Environmental and*

Sustainability Indicators, *19*, 100270. https://doi.org/10.1016/J.INDIC.2023.100270

Noth, F., & Rehbein, O. (2019). Badly hurt? Natural disasters and direct firm effects. *Finance Research Letters*, *28*, 254–258. https://doi.org/10.1016/J.FRL.2018.05.009

Odersky, M., & Löffler, M. (2024). Differential Exposure to Climate Change? Evidence from the 2021 Floods in Germany. *Journal of Economic Inequality*, *22*(3), 551–576. https://doi.org/10.1007/S10888-023-09605-6/METRICS

Paglialunga, E., Coveri, A., & Zanfei, A. (2022). Climate change and within-country inequality: New evidence from a global perspective. *World Development*, *159*, 106030. https://doi.org/10.1016/J.WORLDDEV.2022.106030

Palagi, E., Coronese, M., Lamperti, F., & Roventini, A. (2022). Climate change and the nonlinear impact of precipitation anomalies on income inequality. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(43), e2203595119. https://doi.org/10.1073/PNAS.2203595119/SUPPL_FILE/PNAS.2203595119.SAPP.PDF

Quiroga, S., & Suárez, C. (2016). Climate change and drought effects on rural income distribution in the Mediterranean: A case study for Spain. *Natural Hazards and Earth System Sciences*, *16*(6), 1369–1385. https://doi.org/10.5194/NHESS-16-1369-2016,

Ranasinghe, R., Ruane, A. C., Vautard, R., Arnell, N., Coppola, E., Cruz, F. A., Dessai, S., Saiful Islam, A. K. M., Rahimi, M., & Carrascal, D. R. (2021). *Climate change information for regional impact and for risk assessment*.

Reaños, M. A. T. (2021). Floods, flood policies and changes in welfare and inequality: Evidence from Germany. *Ecological Economics*, *180*, 106879.

Roson, R., & Sartori, M. (2016). Estimation of Climate Change Damage Functions for 140 Regions in the GTAP 9 Data Base. *Journal of Global Economic Analysis*, *1*(2), 78–115. https://doi.org/10.21642/JGEA.010202AF

Sakai, Y., Estudillo, J. P., Fuwa, N., Higuchi, Y., & Sawada, Y. (2017). Do Natural Disasters Affect the Poor Disproportionately? Price Change and Welfare Impact in the Aftermath of Typhoon Milenyo in the Rural Philippines. *World Development*, *94*, 16–26. https://doi.org/10.1016/J.WORLDDEV.2016.12.036

Sartori, M., Geneletti, D., Schiavo, S., & Scolozzi, R. (2017). To What Extent Will Climate and Land-Use Change Affect EU-28 Agriculture? A Computable General Equilibrium Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3038311

Sedova, B., Kalkuhl, M., & Mendelsohn, R. (2019). Distributional Impacts of Weather and Climate in Rural India. *Economics of Disasters and Climate Change 2019 4:1*, *4*(1), 5–44. https://doi.org/10.1007/S41885-019-00051-1

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. Di, Ghosh, S., Iskandar, I., Kossin, J., & Lewis, S. (2021). *Weather and climate extreme events in a changing climate*.

Shao, L. F. (2021). Robust determinants of income distribution across and within countries. *PLOS ONE*, *16*(7), e0253291. https://doi.org/10.1371/JOURNAL.PONE.0253291

Sobhee, S. K. (2020). Greater Female Employment Participation as a Catalyst to Reducing Income Inequality in Developing Countries – The Case of Latin American and Sub-Saharan African Countries. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3741992

Soci, C., Hersbach, H., Simmons, A., Poli, P., Bell, B., Berrisford, P., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Radu, R., Schepers, D., Villaume, S., Haimberger, L., Woollen, J., Buontempo, C., & Thépaut, J.-N. (2024). The ERA5 global reanalysis from 1940 to 2022. *Quarterly Journal of the Royal Meteorological Society*, *150*(764), 4014–4048. https://doi.org/10.1002/QJ.4803

Tesselaar, M., Wouter Botzen, W. J., Haer, T., Hudson, P., Tiggeloven, T., & Aerts, J. C. J. H. (2020). Regional Inequalities in Flood Insurance Affordability and Uptake under Climate Change. *Sustainability 2020, Vol. 12, Page 8734*, *12*(20), 8734. https://doi.org/10.3390/SU12208734

Thiede, B. C. (2014). Rainfall Shocks and Within-Community Wealth Inequality: Evidence from Rural Ethiopia. *World Development*, *64*, 181–193. https://doi.org/10.1016/J.WORLDDEV.2014.05.028

Thissen, M., Oort, F. Van, & Diodato, D. (2013). *Integration and Convergence in Regional Europe: European Regional Trade Flows from 2000 to 2010*. https://www.econstor.eu/handle/10419/124122

Tovar Reaños, M. A. (2021). Floods, flood policies and changes in welfare and inequality: Evidence from Germany. *Ecological Economics*, *180*, 106879. https://doi.org/10.1016/J.ECOLECON.2020.106879

Trigo, R. M., Ramos, A. M., Nogueira, P. J., Santos, F. D., Garcia-Herrera, R., Gouveia, C., & Santo, F. E. (2009). Evaluating the impact of extreme temperature based indices in the 2003 heatwave excessive mortality in Portugal. *Environmental Science & Policy*, *12*(7), 844–854. https://doi.org/10.1016/J.ENVSCI.2009.07.007

Vésier, C., & Urban, A. (2023). Gender inequalities in heat-related mortality in the Czech Republic. *International Journal of Biometeorology*, *67*(8), 1373–1385. https://doi.org/10.1007/S00484-023-02507-2/METRICS

Vrontisi, Z., Charalampidis, I., Lehr, U., Meyer, M., Paroussos, L., Lutz, C., Lam-González, Y. E., Arabadzhyan, A., González, M. M., & León, C. J. (2022). Macroeconomic impacts of climate change on the Blue Economy sectors of southern European islands. *Climatic Change*, *170*(3–4), 1–21. https://doi.org/10.1007/S10584-022-03310-5/FIGURES/6

Weynants, M., Ji, C., Linscheid, N., Weber, U., Mahecha, M. D., & Gans, F. (2024). *Dheed: an ERA5 based global database of dry and hot extreme events from 1950 to 2022*. https://doi.org/10.5194/ESSD-2024-396

Yamamura, E. (2015a). The Impact of Natural Disasters on Income Inequality: Analysis using Panel Data during the Period 1970 to 2004. *International Economic Journal*, *29*(3), 359–374. https://doi.org/10.1080/10168737.2015.1020323;CTYPE:STRING:JOURNAL

Yamamura, E. (2015b). The impact of natural disasters on income inequality: analysis using panel data during the period 1970 to 2004. *International Economic Journal*, *29*(3), 359–374.

Yokohata, T., Kinoshita, T., Sakurai, G., Pokhrel, Y., Ito, A., Okada, M., Satoh, Y., Kato, E., Nitta, T., Fujimori, S., Felfelani, F., Masaki, Y., Iizumi, T., Nishimori, M., Hanasaki, N., Takahashi, K., Yamagata, Y., & Emori, S. (2020). MIROC-INTEG-LAND version 1: A global biogeochemical land surface model with human water management, crop growth, and land-use change. *Geoscientific Model Development*, *13*(10), 4713–4747. https://doi.org/10.5194/GMD-13-4713-2020,

Technical Appendix 1

To address the issue of multicollinearity and enable the inclusion of sectoral effects and interactions in our estimated models, we employ Principal Component Analysis (PCA). By generating principal components through PCA, we effectively reduce the dimensionality of the data while preserving the variance, thereby eliminating multicollinearity and enhancing the robustness of our regression model. The PCA results (to be discussed in detail in the final draft), reveal three principal components: PC1 represents a general economic growth factor, encapsulating contributions from all sectors, indicating broad-based economic activity. PC2 exhibits a strong loading for the agricultural sector, highlighting the unique variance attributable to agricultural GDP. PC3 primarily reflects the contrasts between industry and services, capturing the differential growth dynamics and sectoral shifts within the economy. This approach ensures that the regression analysis accurately reflects the underlying economic structures without the distortions caused by multicollinearity.

```
Principal components/correlation                 Number of obs    =      1,962
                                                 Number of comp.  =          3
                                                 Trace            =          3
    Rotation: (unrotated = principal)            Rho              =     1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.84385	2.69954	0.9479	0.9479
Comp2	.144312	.132472	0.0481	0.9961
Comp3	.0118395	.	0.0039	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Unexplained
ln_real_Ag~P	0.5636	0.8170	0.1215	0
ln_real_In~P	0.5873	-0.2930	-0.7545	0
ln_real_Se~P	0.5809	-0.4966	0.6450	0

Based on the results of the principal component analysis (PCA) conducted on the variables $ln\_real\_Agri\_GDP$, $ln\_real\_Ind\_GDP$, and $ln\_real\_Serv\_GDP$, it is recommended to retain only the first principal component (PC1) for subsequent regression analysis. The decision is guided by several key statistical and interpretive criteria. Firstly, PC1 has an eigenvalue of 2.844, which far exceeds the commonly used threshold of 1 under the Kaiser Criterion, indicating that it explains more variance than any single original variable. In fact, PC1 accounts for 94.79% of the total variance, which alone surpasses the 85-90% cumulative variance threshold typically sought in dimensionality reduction exercises. This suggests that PC1 effectively captures the vast majority of the information contained in the original dataset.

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Furthermore, the component loadings for PC1 are relatively balanced across all three GDP variables (0.5636 for Agriculture, 0.5873 for Industry, and 0.5809 for Services), indicating that it represents a general economic growth factor encompassing contributions from all sectors. This balanced loading pattern reinforces the interpretability of PC1 as a comprehensive indicator of overall economic activity, making it both statistically robust and economically meaningful. In contrast, PC2 and PC3 explain only 4.81% and 0.39% of the variance, respectively, which are minimal contributions that do not justify their inclusion. PC2, while showing a strong loading for the agricultural sector, does not add significant explanatory power, and PC3's variance contribution is negligible.

Considering both the statistical evidence and the economic interpretability of the components, retaining only PC1 ensures that the regression model remains parsimonious without compromising on the explanatory power. This approach minimizes potential issues related to overfitting and multicollinearity while maintaining the core informational value derived from the original GDP variables.

Technical appendix 2

To ensure comparability in the assessment of extreme temperature events, heatwave and coldwave calculations are conducted over the full calendar year (January to December, NF13). Heatwaves are identified using the Excess Heat Factor (EHF), while coldwaves are characterised by the Excess Cold Factor (ECF). These indices account for both short-term anomalies - where current temperatures deviate from recent averages, and long-term anomalies, where temperatures exceed historical thresholds based on the 1980–2010 reference period.

A heatwave day is flagged when the daily maximum or mean temperature, if $T_d > T_{90}$ or $T_d > T_{95}$), exceeds either the 90th or 95th percentile (T_{90} or T_{95}) of the reference period. To formally capture both short-term and long-term heat stress, the Excess Heat Factor (EHF) is calculated as:

$$EHF_d = EHI_{sig,d} * \max(1, EHI_{acc,d})$$

where $EHI_{sig,d} = T_d - T_{90} \; or \; T_d - T_{95}$, reflects long-term deviation; $EHI_{acc,d} = T_d - \overline{T_{3d}}$ captures short-term deviation relative to the preceding three days' mean temperature. A heatwave event is declared when EHF > 0 for at least three consecutive days.

Similarly, a coldwave day is flagged when T_d falls below the 10th or 5th percentile, if $T_d < T_{10}$ or $T_d < T_5$, of the reference period. The Excess Cold Factor (ECF) is calculated as:

$$ECF_d = ECI_{sig,d} * \max(1, ECI_{acc,d})$$

where $ECI_{sig,d} = T_{10} - T_d \; or \; T_5 - T_d$, indicates long-term cold deviation; $ECI_{acc,d} = \overline{T_{3d}} - T_d$ captures short-term deviation of coldwave. A coldwave event is defined as ECF > 0 for at least three consecutive days.

The intensity of heatwaves and coldwaves is measured using two distinct approaches: (i) amplitude, which captures the peak temperature of the most extreme heatwave or coldwave within a given year, and (ii) magnitude, which reflects the average intensity across all such events throughout the year. Frequency is evaluated through three metrics: (i) frequency, defined as the total number of heatwave or coldwave days recorded nationwide in a given year; (ii) duration, referring to the length of the longest heatwave or coldwave event within the year; and (iii) number, which counts the total number of distinct heatwave or coldwave events.

This study aims to assess the effects of heatwaves and coldwaves on income inequality both across and within countries. Due to the absence of an index that captures the spatial concentration of extreme temperature events within subnational regions, we adopt magnitude as the preferred measure of intensity. For frequency, we rely on number, as it captures the count of individual events occurring annually.

The number of heatwave events is defined as follows: let $HW_{i,t}$ denote each identified heatwave event in country i and year t, then

$$Number\_HW_{i,t} = count(HW_{i,t})$$

where the duration of each heatwave $HW_{i,t} \geq 3$ days and for all days $d \in HW_{i,t}$, the the Excess Heat Factor $EHF_d > 0$.

The magnitude of heatwaves is defined as the mean EHF across all days of the event:

$$Magnitude\_HW_{i,t} = \frac{1}{n}\sum_{d=1}^{n_i} EHF_d$$

Similarly, for coldwaves, let $CW_{i,t}$ denote each identified coldwave event in country i and year t, then

$$Number\_CW_{i,t} = count(CW_{i,t})$$

where the duration of each coldwave $CW_{i,t} \geq 3$ days and for all days $d \in CW_{i,t}$, the Excess Cold Factor $ECF_d > 0$.

The magnitude of coldwaves is defined as the mean ECF across all days of the event:

$$Magnitude\_CW_{i,t} = \frac{1}{n}\sum_{d=1}^{n_i} ECF_d$$

In instances where no valid event occurs within a given year, the values are recorded as, $Number\_HW_{i,t} = 0$, $Number\_CW_{i,t} = 0$, $Magnitude\_HW_{i,t} = NA$, and $Magnitude\_CW_{i,t} = NA$.

The calculation methods for the other extreme weather events, including icing days (when the daily maximum temperature remains below 0°C), hot days (when the daily maximum temperature exceeds 35°C), and rainfall days (when daily precipitation surpasses 10 mm), rely on two key metrics. The annual area-weighted number of days represents the total number of days in a year when the specified condition is met, weighted by the affected area[2], while the mean affected area (in km²) indicates the average land area within a country experiencing the extreme event, denoted as $icingdays$, $hotdays$, $R10mmdays$, $mean\_icingdays\_area$, $mean\_hotdays\_area$, and $mean\_R10mmAGdays\_areast$, respectively. However, as this study assesses the impacts of extreme weather events across countries, differences in land area accounts for, as the scale and effect of an affected area in the United Kingdom would differ from that in China. To ensure comparability, standardising the affected area by total country size provides a more

[2] For heavy precipitation, we only weighted by the affected agricultural land size.

meaningful measure. Accordingly, the standardised metrics, denote as $mean\_icingdays\_areast$, $mean\_hotdays\_areast$, and $mean\_R10mmdays\_areast$, represent the adjusted area-weighted mean affected area, respectively.

The modelling choice to include only the interaction term between event frequency and intensity, while omitting the individual terms, is grounded in both theoretical and econometric considerations. Theoretically, the socioeconomic impact of extreme climate events is highly nonlinear and contingent on events being both frequent and severe; changes in frequency or intensity alone often cannot fully capture the resulting effects on inequality and vulnerability (Hsiang et al., 2017; Parmesan et al., 2022). Mechanistically, frequent yet mild disturbances produce different cumulative effects than rare but extreme events, necessitating an interaction term to reflect the compound nature of climate risk (Kahn et al., 2005). Econometrically, including only the interaction helps mitigate multicollinearity between intensity and frequency, which often co-vary in climate data (Dell et al., 2014), and improves model identification by concentrating explanatory power on joint extremes. This parsimonious specification is particularly appropriate in cross-country panel analyses, where model simplicity enhances comparability and interpretability (Burke et al., 2015). Overall, the interaction term offers a more precise and policy-relevant measure of climate-driven inequality and resilience. denote as HW_IF, CW_IF, $Icing\_IF$, Hot_IF, and $R10mm\_IF$.

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Technical appendix 3

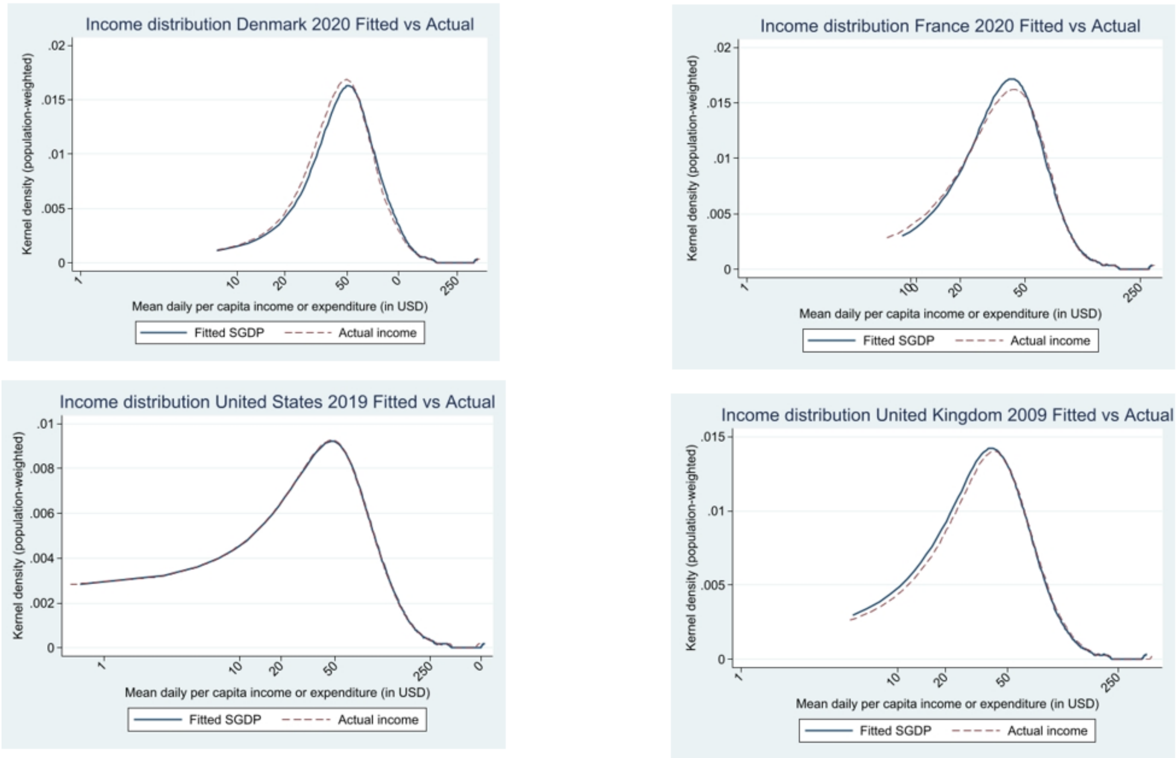

Figure 1A: Overlay of predicted and observed income levels by percentile for selected countries.

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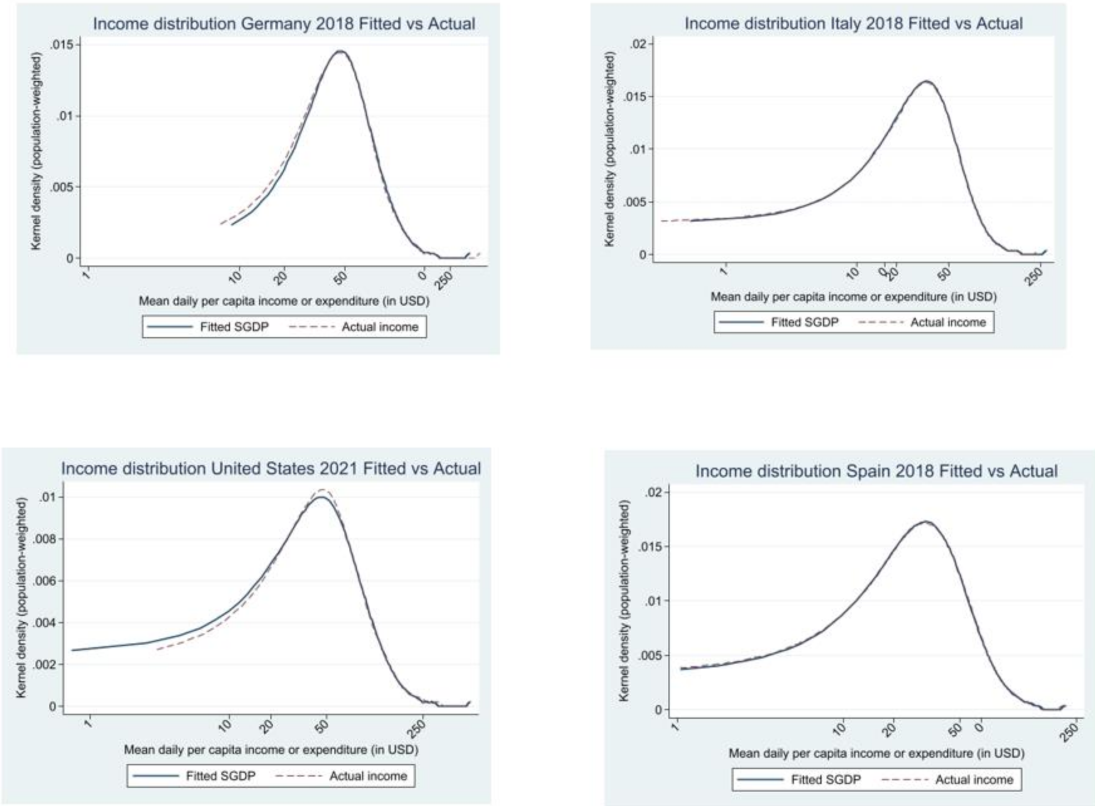

Figure 1A: Overlay of predicted and observed income levels by percentile for selected countries. (cont)

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