Subnational projections of poverty and income distribution to support climate risk assessments: A CGE-spatial microsimulation approach

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https://cran.r-project.org/web/packages/stacr/vignettes/getting-started.html https://drmkc.jrc.ec.europa.eu/risk-data-hub#/atlas/metadata/coastal_flood

1 Introduction

There is ample evidence that climate change conditions are increasingly worsening in Europe (Copernicus Climate Change Service (C3S) and World Meteorological Organization (WMO), 2025). Since the 1980s, the continent has been the fastest warming region in the world and 2024 marked the first year that the global average temperature exceeded the Paris Agreement target of 1.5°C above the pre-industrial level. Equally, there are strong indications that extreme climate events are becoming more frequent and intense. In 2024, almost one third of rivers in Europe experienced flooding, the highest share in over 10 years. In the same year, more and longer heatwaves were also observed, with the most extreme and longest ones occurring in southeastern Europe. The frequency and intensity of climate extremes in Europe is projected to increase, regardless of the level of global warming (Bednar-Friedl et al., 2022). Extreme weather events have considerable impacts on human health, livelihoods and well-being, particularly for vulnerable populations such as low-income households, the elderly and children.

A number of studies have assessed expected future exposure to extreme climate in Europe. However, most studies only combine population maps with spatially explicit information on hazards to determine the share of the population at risk. Therefore, they do not provide a complete climate risk assessment as vulnerability (for which poverty is a reasonable proxy) is not taken into account. Both COVID and current geopolitical tensions have shown that the future is highly uncertain and global shocks can have dramatic consequences on future socio-economic development and global poverty, thereby affecting the future vulnerability and risk of people from climate shocks. The preparation of comprehensive climate risk assessments requires a scenario approach that presents a variety of poverty projections to take these uncertainties into account.

The aim of this study is to undertake comprehensive climate hazard risk assessment for the EU by using an innovative approach that combines CGE model output with the Microsimulation of Income DynamicS (MIDS), which uses a spatial microsimulation approach to project future poverty at the subnational scale under differen scenarions. These maps are combined with climate hazards to identify the number and profile of the most vulnerable people as well as high-risk hotspots. As such, it aims to bridge the scales between (a) climate impact and vulnerability research, which requires data with detailed spatial resolution, and (b) integrated assessment modelling, which mainly uses macro-level approaches to simulate change in socio-economic indicators.

The model simulation approach outlined in this paper has links with the literature on poverty mapping, which uses a variety of approaches to quantify the geographical distribution of income and poverty within a country or region. The most common approach to create poverty maps is small area estimation (Elbers et al., 2003; Molina et al., 2010), which uses econometric techniques to estimate poverty indicators at the subnational level by combining information from household surveys and population census. Spatial microsimulation is an alternative approach (Anderson, 2013; Panori et al., 2017; Tanton, 2011), which involves optimization. It is therefore better suited for scenario simulation exercises, which aim to capture the impact of long-run spatial (e.g. urbanization and the shift from agricultural to manufacturing and services workers) and macro (population and GDP growth) drivers on household income, and provides a natural link with macro-economic simulation approaches that are used for poverty and climate impact assessments (Hallegatte et al., 2017; Laborde Debucquet et al., 2018).

2 Methods and materials

2.1 Methodological framework

Long-run income changes at the household level are the outcome of a complex interaction of local (e.g. demography and degree of urbanization), national (e.g. structural transformation of the economy and redistributive policies) and global (e.g. climate change, trade, pandemics and wars) driving forces (Acemoglu et al., 2002; Burke et al., 2015; Dollar et al., 2016; Mahler et al., 2022). To capture these factors, the MIDS model, combines spatial microsimulation (Tanton et al., 2013) with micro-macro simulation approaches (Bourguignon et al., 2013; Ruijven et al., 2015) to project income distribution and income change at the subnational level.

Spatial microsimulation is a method to model and analyze population dynamics at a small geographic scale, such as districts, municipalities and provinces. It involves combining household level information from surveys with aggregate population and demographic statistics (referred to as 'constraint' variables) from a population census to derive household weights that reproduce the characteristics of the actual population in a small area (Lovelace et al., 2016). The weights are then combined with the survey data to simulate the distribution of the target variable (in this case household income) for that area. Spatial microsimulation has been used to analyze the geographical distribution of poverty, health, transport and housing (Tanton et al., 2013). Spatial microsimulation models are a useful tool to inform regional policies and rural-urban planning as they provide information at spatial levels for which only scarce and fragmented data is available.

To project the spatial distribution of household income distribution over time, MIDS updates both the weight and the income level of each household into the future. The household weights are adjusted in such a way that the (sub)national population totals are consistent with the (sub)national age, sex, occupation and urban-rural projections that are prepared as part of socio-economic scenarios and which can be considered as the main drivers of change in income distribution (see below). To capture the impact of these drivers on the distribution of income, the reweighting procedure gives higher weights to households with characteristics that are projected to become more dominant in the future and lower weights to households with characteristics that are projected to become less dominant. This means that in scenarios which are characterized by structural economic transformation, the reweighting procedure will allocate higher weights to households with members that are active in manufacturing and services in comparison to households that work in agriculture. Similarly, urbanization and aging of the population are simulated by giving higher weights to urban households (relative to rural households) and households with a large share of elderly family members, respectively.

Apart from changes in the composition of the population, which are captured by the reweighting procedure, growth in (subnational) income distribution will also be affected by changes in the level of household income over time. MIDS distinguishes between two channels that affect household income. The first are changes in factor income, in particular from labor, which is shaped by macro-drivers such as technological progress (e.g. farmers using tractors instead of animal traction), changes in the demand for labor (e.g. an increase in the demand for high-skilled labor) and changes in the supply of labor (e.g. a growing or aging population). Similar to micro-macro poverty studies (Ahmed et al., 2020; Bussolo, De Hoyos, et al., 2010; Laborde Debucquet et al., 2018), MIDS uses the output from a global Computable General Equilibrium (CGE) model (MAGNET) to simulate the impact of macro-drivers on factor income. The advantage of a global simulation model is that it accounts for the impact of global shocks and events, (e.g. trade barriers and climate change impact) that are transmitted through international trade, on national economic development. The second channel that influences household income are policies (e.g taxes, subsidies and pension systems) to redistribute income. To model these, MIDS includes the option to simulate a flat household income tax, which is used to fund a basic income and pension.

Finally, the updated weights and household income are combined to project the simulated future income distribution and poverty at the spatial level. Figure 1 depicts the MIDS modelling framework and the two major channels that determine future household income distribution and poverty. The following sections provide detailed information on key components of the MIDS model and the data.

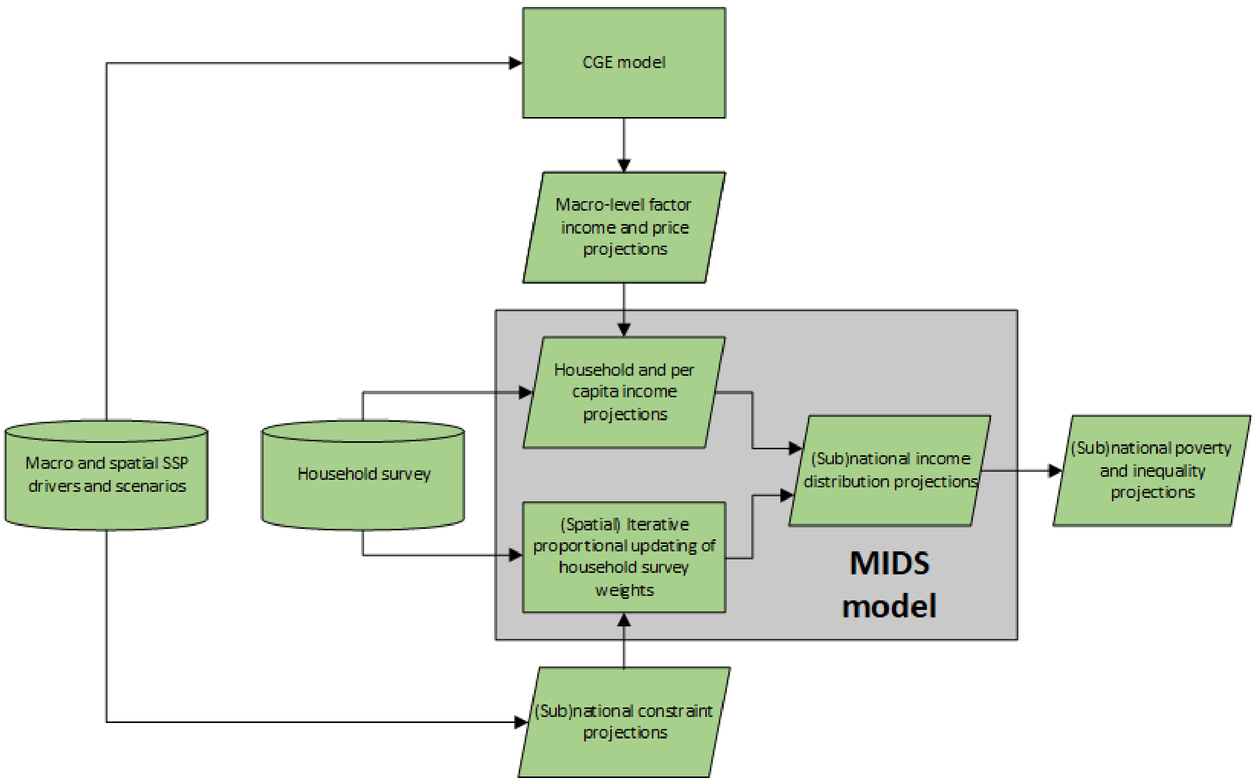

Figure 1: MIDS modelling framework.

The core of MIDS is a dynamic spatial microsimulation approach to account for spatial drivers of household income change over time. More specifically, the model implements a 'pseudo-dynamic' approach (Harding et al., 2011; Tanton, 2014; Vidyattama et al., 2010), which combines a household survey with constraints that are projected into the future. For each period, new household weights were derived using the iterative proportional updating (IPU) algorithm (Ye et al., 2009), which takes into account both household and household member characteristics.

A key assumption in spatial microsimulation is that the constraints are strong predictors for the variable of interest, in this case household income, for which data is only available in the survey. For our study, we selected five constraint variables: occupation, urban-rural status, age, sex and number of households. Occupation is strongly related to a person's level of education and skill-level at work, which jointly are key drivers of wage and income (Beyer et al., 1989; Gibbons et al., 2005). The distribution of occupations is also related to the process of structural economic transformation in which people move from low-skilled jobs in agriculture to high-skill jobs in manufacturing and services (Duernecker et al., 2022; Syrquin, 1988). Accounting for change in the distribution of occupations over time by updating survey weights will capture the impact of structural change on income distribution. We distinguished between five major occupations following the major International Standard Classification of Occupations (ISCO): professionals, technicians, clerks, service workers and agricultural & craft workers and three additional classes: elderly (65 years and above), children (under 15 years) and adults not in the labor force (students and adults unable or unwilling to pursue paid work), which together describe the total population.

Urbanization is another important determinant of household income. Several studies describe the existence of a persistent urban-rural wage gap, which is explained by differences in skill level between urban and rural workers (Young, 2013) as well as market failures (Munshi et al., 2016). We used two classes (urban and rural) to incorporate urbanization in the model.

Sex and age are key variables that describe the demographic change of the population. Adding these as constraints captures the impact of differences in income between young and old workers and between male and female workers and how this impacts income distribution as a consequence of demographic change. Including age and sex also ensures consistency between MIDS and population projections, which are a key driver of the macro-simulation model that informs MIDS. We distinguished between two sexes (male and female) and seven age classes. Similar to Hallegatte et al. (2017), we decided to exclude the number of children in a household from the re-weighting procedure and proportionally rescale the number of children (age <15) per household after the simulation to match the subnational projections for the age class of under 15. The reason for doing this is that the household survey contains a very low number of households with a small number of children, which makes it difficult to calibrate weights for low population growth scenarios.

Finally, to maintain the link between income, which is determined at the household level and demographic change, which is determined by the family member structure, we added the number of households as a constraint in the reweighting procedure.

2.2 Macro-drivers of income change

We used macro-level projections for changes in labor income from the MAGNET model to update household-level income information in MIDS. MAGNET is a recursive dynamic global CGE model that includes an improved labor market module to simulate the markets and resulting labor income for each of the five major occupation classes under different future scenario projections. To link the MAGNET income projections to MIDS, we decomposed household income from the survey (approximated by total consumption expenditure) in labor and non-labor contributions using a regression approach (Hallegatte et al., 2017). The process involved four steps (see Supplementary Section 5 for details). First, we allocated one of the five major occupation classes to each person in the household, using information from the household survey. Second, we used robust regression, which accounts for the impact of outliers (Andersen, 2008) to estimate the average contribution of each person with a certain occupation to the total labor income of the household. We distinguished between urban and rural populations to control for differences in income sources between both population groups. Third, we combined the estimated coefficients for each occupation class with real labor income change projections from MAGNET and calculated the total labor income for each household in future period. Finally, we scaled the simulated income distribution in such a way that the change in mean income per capita was consistent with the change in real GDP per capita from the SSP projections. The scaling can be regarded as an adjustment factor to account for the change in capital income, which is not captured by our procedure to update household labor income (Bussolo, Hoyos, et al., 2010).

3 Data

3.1 Household survey data

Household survey data is a core data input into MIDS. For the EU, we used the latest wave, spanning the year 2024, of the European Union Statistics on Income and Living Conditions (EU-SILC) survey, which is an annual survey that collects information on income, poverty and living conditions in the EU [Eurostat (2025b)}. EU-SILC data are a key source of information to monitor and coordinate social protection and inclusion policies in the EU. Micro-data is available for the 27 EU Member States as well as Norway and Switzerland. The surveys include data for between 3,000 and 7,000 households per country, and are representative at the

EU NUTS (Nomenclature of Territorial Units for Statistics) level 1, which represent a coarser spatial scale than provinces. The EU-SILC surveys include statistics on a wide range of indicators. Most relevant for this study are data on basic household and person characteristics (e.g. urban-rural status, occupation, age and sex), household disposable income and its determinants, especially household member income sources, such as wages and capital rents, which can be linked to the macro-level projections from MAGNET.

3.2 Scenarios and subnational projections

As a basis for our projections we used the Shared-Socioeconomic Pathways (SSPs), a set of socio-economic scenarios that were developed for climate change research (Riahi et al., 2017; Vuuren et al., 2017) but are increasingly used as narratives to guide a range of global assessments (Leclère et al., 2020; Willett et al., 2019). The SSPs consist of five storylines that each describe different future worlds as well as related projections of key drivers (O'Neill et al., 2017). In this study, we limited the analysis to three scenarios: SSP1 (Sustainability), SSP2 (Middle of the road) and SSP3 (Regional rivalry). SSP1 and SSP3 are frequently used in simulation studies because they are regarded as the most extreme socio-economic scenarios, while SSP2 is considered as a business-as-usual or baseline scenario. As the SSP3 narrative does not contain explicit information on intra-country inequality trends, we decided to adopt the SSP4 (Inequality) storyline, which predicts an increase in inequality within economies and therefore refer to this scenario as SSP3/4.

The SSPs mainly describe macro-level storylines and scenarios of future development but provide limited detail on driving forces at spatial and micro scales, which are key determinants of income distribution and poverty. For this reason, we included an additional set of drivers in line with the SSP scenario framework (Table 1). For the macro-level, we used latest update of the standard SSP1-SSP3 GDP and population projections from the SSP scenario database (IIASA, 2025) as input for MAGNET. To capture the spatial dynamics, we created subnational projections for all five constraint variables that we consider as main driving forces of household income distribution at the local-level. To construct the demographic (age and sex), urbanization and structural change (occupation structure) projections, we integrated a wide number of data sources, including high-resolution population data (Pezzulo et al., 2017), subnational labor force statistics (Eurostat, 2025a) and spatially explicit demographic and urbanization SSP projections for the EU (Bonatz et al., 2026). The subnational projections were prepared for all NUTS 2 zones in Europe, spanning the period 2024-2050. Finally, we added SSP-specific assumptions on labor income changes and redistribute policies that have an effect on micro-level (i.e. household and per capita) income.

Table 1: Summary of scenario assumptions at different scales. τ is a flat household income tax that ensures a basic income is transferred to all persons older than 15 years. κ is a flat household income tax to simulate a universal pension for people of age 65 and above. See Supplementary Section 3 for details.

element	SSP1	SSP2	SSP3/4
Macro drivers			
GDP growth	High	Medium	Low
Population growth	Relatively low	Medium	High
Spatial drivers			
Demographic change	Relatively low	Medium	High
Urbanization	High	Medium	Low
Structural change	Rapid	Medium	Low
Micro drivers			
Labour income trends	Neutral	Neutral	Diverging
Basic income cash transfer	Substantial (τ = 40%)	None (τ = 0%)	None (τ = 0%)
Pension cash transfer	Substantial (κ = 20%)	None (κ = 0%)	None (κ = 0%)

4 Results

Typical results from our approach include district-level per capita income distribution and poverty projections for the period 2020-2050 under different socio-economic and climate scenarios. Apart from the total population poverty rate, the household survey data allows us to prepare population headcount estimates for subgroups, including urban-rural status, age group and occupation. Finally, we combine the national poverty maps with climate hazard (e.g. floods, heat stress and cold spells) to identify areas that are both characterized by low-incomes and climate extremes. Figure 2 presents an example of the exposure of poor people to heat stress in Ethiopia from a previous study. We are currently preparing a similar analysis for the European Union but looking at a wider range of climate hazards, including floods, heat stress and cold spells that are expected to affect countries in Europe in the coming decades (Dosio et al., 2023).

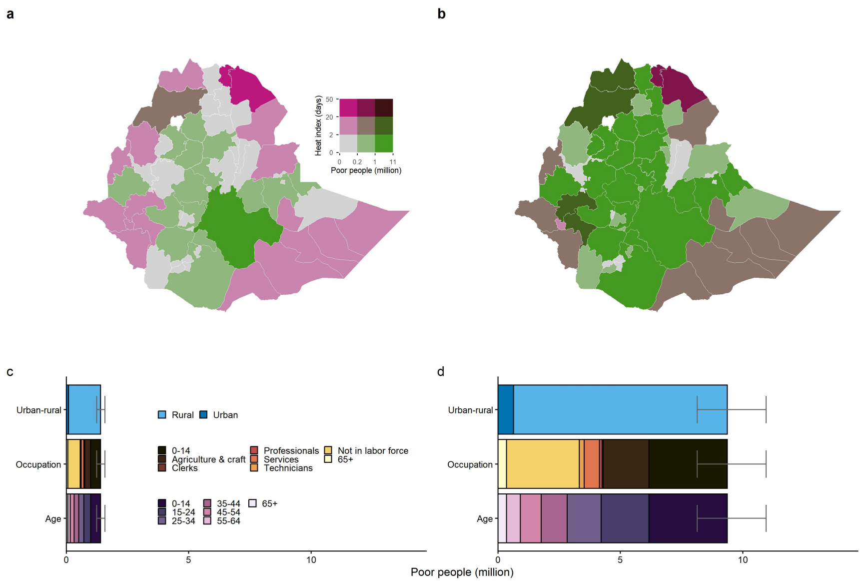

Figure 2: (a) Overlay of SSP poverty headcount and RCP HI maps for 2050 (SSP2-RCP4.5 and SSP3/4-RCP7.0). Heat stress is measured as the number of consecutive days with a HI of above 41°C. (b) Number of poor people exposed to a heat wave (measured as a HI of two or more consecutive days above 41°C) by urban-rural status, occupation class and age structure. The error bars indicate climate model uncertainty.

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