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# High-resolution income projections over the 21st century in Europe consistent with the Shared Socioeconomic Pathways

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## LETTER

## High-resolution income projections over the 21st century in Europe consistent with the Shared Socioeconomic Pathways

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E-mail: [mehdi.mikou@universite-paris-saclay.fr](mailto:mehdi.mikou@universite-paris-saclay.fr)**Keywords:** high-resolution, income, projections, SSPSupplementary material for this article is available [online](#)**Abstract**

Climate risk in Europe is unevenly distributed among the population and is projected to increase substantially over the 21st century due to evolving climatic and socioeconomic conditions. Projections of vulnerability drivers, such as income distribution, are needed for assessing future climate risk. In Europe, existing studies typically rely on inadequate proxies, such as gross domestic product per capita, to account for future vulnerability associated with income levels. This study presents a novel top-down iterative methodology to produce decadal, high-resolution (1 km) maps of disposable income across Europe for the 21st century consistent with the Shared Socioeconomic Pathways (SSPs). More specifically, our method aligns with SSP narratives on future economic growth, income distribution, population dynamics and settlement expansion. We illustrate two possible applications of these projections by analysing future shifts in income distribution and estimating the evolution of the number of people at risk of poverty across different development pathways. In highly unequal pathways (SSP3 and SSP4), poverty levels across Europe are projected to increase significantly, with over 30% of the population at risk of poverty by 2100. On the other hand, pathways with high economic growth, specifically SSP1 and SSP5, result in a decrease in poverty rates. This dataset can serve as a resource for examining future vulnerabilities to climate change and socioeconomic inequalities, providing valuable insights for more effective climate risk assessments and targeted adaptation strategies.

**1. Introduction**

Human-induced greenhouse gas emissions are driving the rise in global temperatures and altering the frequency, intensity, and extent of extreme climate events [1]. Climate change is reshaping the distribution of climate risks, which arise from the interactions between hazards, vulnerability, and population exposure [2]. While changes in climatic conditions play a crucial role in determining future climate risks, these risks are also shaped by shifts in exposure and vulnerability driven by policies modelled within development pathways. For instance, socioeconomic inequalities, such as wealth and income, influence vulnerability [3]. To accurately assess the evolution of climate risk, it is essential to account for the

temporal dynamics of all its components, including vulnerability and exposure. Although climate projections are often spatially detailed, vulnerability factors are usually represented at a coarse resolution. Some studies have even used static maps of current socioeconomic variables, applying present-day data to future scenarios without accounting for future changes [4, 5].

The Shared Socioeconomic Pathways (SSPs), developed by the climate change research community, depict five different future development pathways: sustainability (SSP1), middle of the road (SSP2), regional rivalry (SSP3), inequality (SSP4), and fossil-fuelled development (SSP5) [6, 7]. These qualitative narratives were further detailed to generate quantitative country-level estimates of vari-

ous socioeconomic variables such as population, gross domestic product (GDP) growth, or trends in urbanisation [8–10]. Therefore, they provide helpful information for studying how future changes in socioeconomic conditions might affect the future exposure and vulnerability of the population to climate change [5]. While the SSP are widely used in climate research, refining their application at regional and local scales is essential for impact studies. A significant technical challenge lies in ensuring the consistency of regional/local scale projections with global socioeconomic narratives [11].

Several studies have developed high-resolution spatiotemporal datasets of economic variables aligned with the SSP at global or continental scales. For example, researchers have downscaled GDP to a 1/12 degree resolution by accounting for economic and spatial interactions between cities across the five SSP [12]. SSP-consistent maps of GDP at 1 km resolution have been generated in countries covering 60% of the global land surface using population counts and nightlight images as proxies [13]. However, most of these studies do not incorporate projections of inequality, making their future gridded maps not necessarily consistent with the economic disparities outlined in the SSP [14]. Moreover, existing datasets predominantly focus on GDP, which does not account for redistribution mechanisms within countries. Therefore, they might overestimate economic spatial inequality compared to disposable income-based maps.

In this study, we generated decadal disposable income maps throughout the 21st century across the five SSP, using a newly developed 1 km gridded income dataset for Europe in 2015 [15]. Disposable income refers to the portion of household income available for consumption or savings. Although both disposable income and GDP aggregate various forms of income, disposable income offers the advantage of accounting for redistribution mechanisms within countries, thereby providing a more accurate reflection of household living standards. Additionally, GDP figures can be artificially inflated in tax havens (by companies transferring all their benefits to specific countries), potentially distorting cross-country economic comparisons [16]. For these reasons, income—and more specifically, disposable income—serves as a more accurate indicator of social vulnerability for populations exposed to extreme climate events. Our methodology employs a top–down iterative approach that ensures quantitative consistency between several SSP socioeconomic datasets: economic growth [8, 17], income inequality [14], national income distribution [18] available at a national scale along gridded population [19], and settlement extension projections [20, 21]. These projections offer a framework for examining changes in income distribution across European countries

throughout the 21st century under the five SSP scenarios. We illustrate two possible applications of the dataset by assessing future spatial shifts in income distribution and estimating the evolution of the population at risk of poverty under each SSP scenario. This dataset can enhance our understanding of future climate risk, which is critical for developing adaptation policies and effectively protecting the European population from the impacts of climate change.

## 2. Materials and methods

### 2.1. Research setup and data processing

We generated the first SSP-consistent disposable income maps for the 21st century, using a combination of 1 km resolution gridded datasets and nationally aggregated economic indicators detailed in table 1. These income maps were developed iteratively using a top–down methodology presented in the four-step workflow outlined in figure 1. The first step consisted of deriving per capita future income growth rates from GDP growth rates. In the second step, we estimated the future pixel-level income distribution using a dataset informing on the share of income captured by each decile. This income distribution was then used to compute decile-level income growth rates that we applied to pixels according to their corresponding decile. Finally, we adjust the obtained income maps to account for future settlement expansion or shrinkage in the projections.

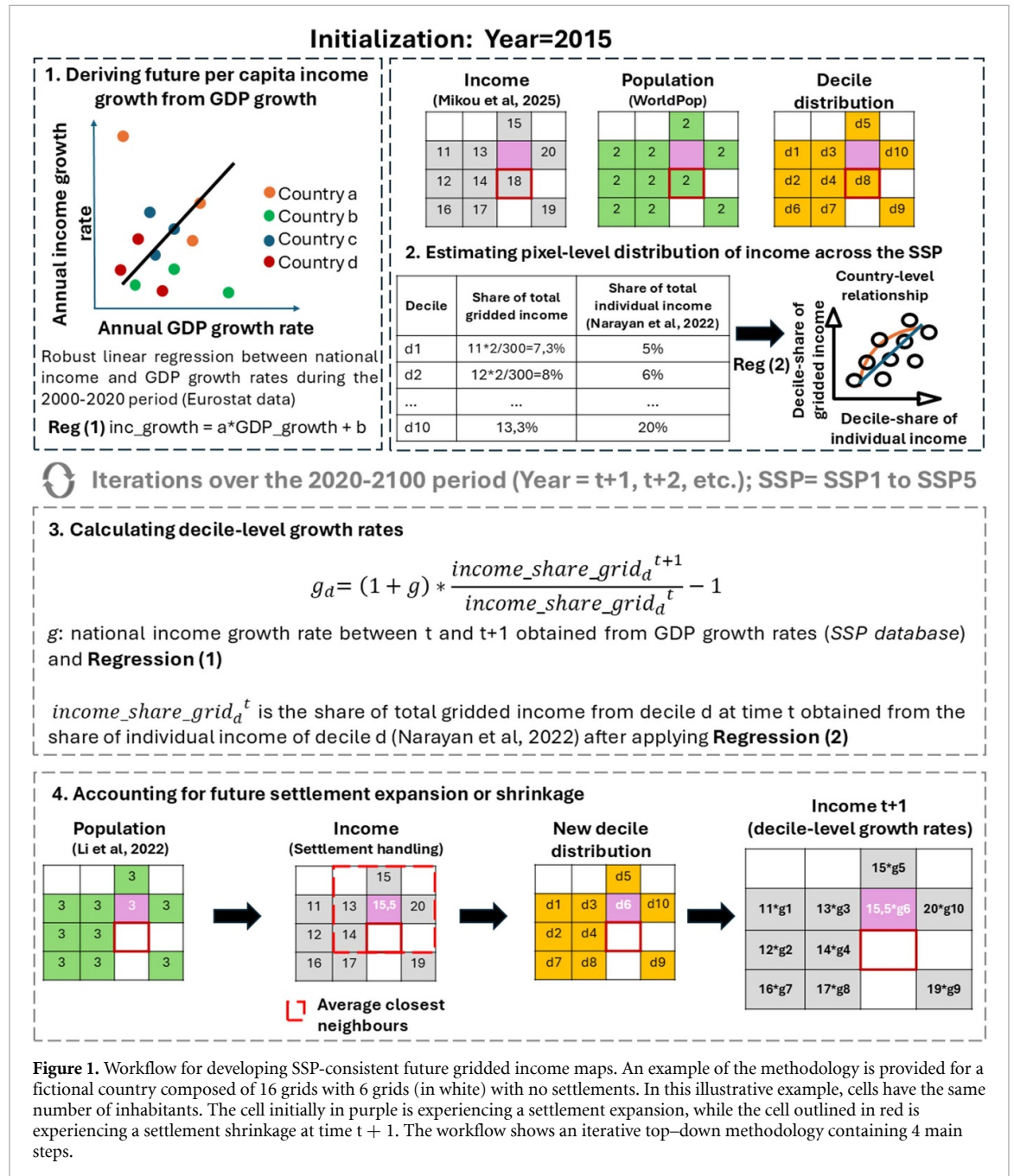
### 2.2. Deriving future per capita income growth from GDP growth

Disposable income and GDP can be used to measure socioeconomic conditions, yet they differ in some aspects [24]. For example, disposable income includes income received by resident households from abroad, which is not part of GDP. Conversely, some domestically generated income (part of GDP) can flow out to non-resident households or companies. These differences have resulted in notable differences in growth rates for GDP and disposable income across OECD countries from 1995 to 2019 [24]. Before the 2007 financial crisis, GDP generally grew faster than disposable income. However, after the crisis, disposable income growth rates exceeded GDP growth rates in more than half of the OECD countries. The divergence in growth rates between median household income and GDP per capita was comprehensively examined by Nolan *et al* [25]. Their analysis underscores that the observed disparities in growth rates can be attributed to a combination of factors, including the application of distinct price deflators and the conceptual discrepancies in measuring income within national accounts versus household surveys.

For this reason, we translated country-level GDP growth rates of the SSP to disposable income growth

**Table 1.** Datasets used to produce 1 km gridded maps of disposable income aligned with the SSP.

Indicator	Resolution	Year	SSP	References	Source
Disposable income	1 km	2015	—	[15]	[22]
Decile-level share of income	National	2020–2100 (every 10 years)	SSP1-SSP2-SSP3-SSP4-SSP5	[18]	[23]
GDP growth rate	National	2020–2100 (every 5 years)	SSP1-SSP2-SSP3-SSP4-SSP5	[8]	SSP scenario 2.0
Population	1 km	2020–2100 (every 10 years)	SSP1-SSP2-SSP3-SSP4-SSP5	[19]	Geosimulation



**Figure 1.** Workflow for developing SSP-consistent future gridded income maps. An example of the methodology is provided for a fictional country composed of 16 grids with 6 grids (in white) with no settlements. In this illustrative example, cells have the same number of inhabitants. The cell initially in purple is experiencing a settlement expansion, while the cell outlined in red is experiencing a settlement shrinkage at time t + 1. The workflow shows an iterative top-down methodology containing 4 main steps.

rates, using past observations available for 27 EU countries out of 38 countries. Predicting income growth rates (in contrast with income levels) ensures that future growth rates remain within the range of historical observations, thereby minimizing extrapolation risks and ensuring greater reliability [26].

In contrast, a regression based on income and GDP levels is less reliable, as the high GDP levels implied by the SSP at the end of the century fall outside the historical range of the observed data. After performing a Pearson correlation test [27] between both variables at the European level (the test was also performed for

individual countries), we fitted a robust linear regression to derive a relationship between both growth rates, using country-level growth rates of per capita GDP ([https://ec.europa.eu/eurostat/databrowser/view/nama\\_10\\_gdp/](https://ec.europa.eu/eurostat/databrowser/view/nama_10_gdp/)) and per capita disposable income ([https://ec.europa.eu/eurostat/databrowser/view/NAMA\\_10R\\_2HHINC/](https://ec.europa.eu/eurostat/databrowser/view/NAMA_10R_2HHINC/)) of the 27 EU countries on the 2000–2020 period. We opted for robust linear regression as it minimises the influence of outliers, which can appear in the data because of economic crises [28]. Regression coefficients were then used to derive per capita disposable income growth rates from SSP GDP projections [8]. Additionally, a 95% confidence interval on the regressed parameters was calculated to assess the sensitivity of the obtained results.

### 2.3. Estimating the pixel-level distribution of income across SSP

The future distribution of income was quantified using inequality metrics developed within the SSP. Qualitative narratives of the SSP on inequality have been used to estimate future country-level inequality estimates of the Gini coefficient [14]. Narayan *et al* (2023) recently proposed a method to generate projections of the share of national income captured by deciles across the 5 SSP [18], using national Gini projections (along with other data inputs). These datasets inform us of future inequalities between individuals within each country. However, it differs from pixel-level inequalities (calculated as the average income of multiple individuals within a pixel), which is required to produce future income maps. Indeed, the disparity between groups of individuals (such as pixels) is always lower than the inequality between individuals [29]. From the Narayan *et al* (2023) dataset [18], we devise a methodology to estimate the share of national income captured by pixel-level deciles.

Using gridded income [15] and population maps [30] available for 2015 (SSP baseline year), we calculated the share of pixel-level income captured by each decile for each European country. Gridded income was constructed from fiscal administrative data and relates to the income of all households living in a specific grid, even if they work outside the grid. In each country, the pixel-level distribution of income was then fitted to the individual distribution of income using either a linear or a logarithmic regression (the choice between both regression methods was made based on the  $R^2$  coefficient). We assumed that the parameters of the regressions were constant across the entire period (2015–2100) and applied, in each country separately, the obtained equation to estimate the share of income captured by each decile at the pixel level. For some countries, we marginally rescaled the obtained shares so that they exactly summed up to one. A 95% confidence interval was also calculated

on the country-level regressed parameters to test the influence of this step on the future gridded income maps.

### 2.4. Calculating decile-level income growth rate

The calculation of income growth within each decile, between two 10 year time periods, was carried out iteratively, using the income growth rate obtained at step 1 and the pixel-level share of income captured by each decile obtained at step 2. The decile-level income growth rate ( $g_d$ ) between time  $t$  and  $t + 1$  was calculated from the following equations, starting with the global country-level income growth rate:

$$g = \frac{\text{avg\_income}^{t+1}}{\text{avg\_income}^t} - 1 \quad (1)$$

The average income of decile  $d$  is given by:

$$\text{avg\_income}_d^t = \frac{\text{avg\_income}^t \cdot \text{income\_share}_d^t}{0.1} \quad (2)$$

Incorporating equation (2) in equation (1) gives:

$$g = \frac{\left( \frac{\text{avg\_income}_d^{t+1} \times 0.1}{\text{income\_share}_d^{t+1}} \right)}{\left( \frac{\text{avg\_income}_d^t \times 0.1}{\text{income\_share}_d^t} \right)} - 1 = \frac{\text{avg\_income}_d^{t+1} \times \text{income\_share}_d^t}{\text{avg\_income}_d^t \times \text{income\_share}_d^{t+1}} - 1 \quad (3)$$

Hence:

$$g_d = \frac{\text{avg\_income}_d^{t+1}}{\text{avg\_income}_d^t} - 1 = (1 + g) \cdot \frac{\text{income\_share}_d^{t+1}}{\text{income\_share}_d^t} - 1 \quad (4)$$

where  $g$  is the country-level income growth rate between  $t + 1$  and  $t$ ;  $\text{avg\_income}^t$  the country-level average income at time  $t$ ;  $\text{avg\_income}_d^t$  the average income of decile  $d$  at time  $t$  and  $\text{income\_share}_d^t$  the share of total income at time  $t$  captured by decile  $d$ .

To align the 2015 per capita income data from Dellink *et al* with the currency used in the GDP projections of the SSP [8], we converted the EU27 2015 PPP€ currency into 2017 International US\$ PPP. We then applied this decile-level income growth rate to all pixels corresponding to their respective decile group. The differentiated growth rates across income deciles result in shifts in income distribution over time. Indeed, pixels positioned at the boundary of two decile categories at time  $t$  may move into a different income category at  $t + 1$ , thanks to a mechanism further analysed in the two illustrative applications. These changes in pixel-level income lead to changes in the spatial distribution of income deciles (which can be observed by comparing maps over time).

## 2.5. Accounting for future settlement expansion or shrinkage

Between two time periods, changes in the spatial distribution of population, partly driven by settlement expansion [31], result in a change in the number of populated pixels (those with at least one inhabitant). In the fourth step of our workflow, we identify, for each of the 5 SSP, areas of settlement expansion and shrinkage (using gridded population projections [19]), and we estimate income in all pixels that were not considered as populated during previous iterations. The 1 km gridded population dataset was re-sampled to align with the resolution of the gridded income dataset using the *R* Raster package [32].

The methodology used to estimate income at time  $t + 1$  in newly populated areas is motivated by the first law of geography, stating that ‘everything is related to everything else, but near things are more related than distant things’ [33]. More specifically, we first identified newly populated pixels (appearing at time  $t + 1$ ) and calculated their income at time  $t$  using two standard methods: (1) average income values of their closest neighbours and (2) inverse distance weighting average [34]. For both methods, we first used the closest eight neighbouring pixels and eventually expanded this number if newly populated pixels were in more isolated areas. The income distributions obtained for new settlements with these two methods were highly consistent (S1 figure), and therefore, in the following of this article, we present only the results obtained with the method based on neighbouring pixels.

At the same time, we manually affected NA values (i.e. no data) to pixels that appeared unpopulated at date  $t + 1$  while they were populated at  $t$ . We obtained the final pixel-level income distribution after adding newly populated pixels and removing unpopulated pixels to the initial income distribution at time  $t$ . We then applied the decile growth rates derived from step 3 to this new income distribution. The change in the total number of populated pixels between two periods can affect the new pixel-level income distribution, also contributing to shifting some pixels into different decile categories (this effect adds to the difference in income growth rates mentioned in step 3).

## 2.6. Applications: shifts in income ranking and population at risk of poverty

As explained above, considering settlement expansion or shrinkage in our workflow can lead to ranking shifts in the pixel-level income distribution over time and across the different SSP. This means that some pixels can experience an upward or downward move in the distribution (eventually leading to a change in their corresponding decile). We examined the evolution of the relative ranking of pixels between

2015 and 2100 to understand to what extent countries will experience changes in their income distribution, depending on the SSP. This kind of analysis is essential when studying the evolution of the exposure of income groups to future environmental hazards. If the future (spatial) income distribution hardly changes, future income groups will be similarly exposed to environmental hazards.

Specifically, we calculated a country-level ranking shift indicator (equation (5)) as the population-weighted average of differences in pixel rankings between 2015 and 2100. Pixels were ranked from 0% for the pixel with the lowest income to 100% for the pixel having the highest income. Pixels with a better ranking at  $t + 1$  than  $t$  experienced a positive shift, while those with a relatively lower ranking face a negative change. These changes in ranking may occur either due to different levels of income growth in populated areas or as a result of settlement changes. Countries undergoing substantial settlement expansion or shrinkage between 2015 and 2100 are more likely to experience significant ranking shifts, which can be either positive or negative. The addition or removal of a large number of settlements is likely to alter the ranking of pixels, potentially resulting in high absolute levels of ranking shifts. Logically, this analysis was limited to pixels considered as populated (i.e. population higher or equal to one) across both periods,

$$\text{ranking\_shift}^{N,M} = \frac{\sum_{i \in A^{N,M}} (\text{ranking}_i^M - \text{ranking}_i^N) \cdot \text{pop}_i^N}{\sum_{i \in A^{N,M}} \text{pop}_i^N} \quad (5)$$

where  $\text{ranking}_i^M$  is the ranking of pixel  $i$  (from 0 to 100%) in year  $M$ ;  $\text{pop}_i^N$  is the population of pixel  $i$  in year  $N$  and  $A^{N,M}$  is the set of pixels having a population higher than 1 in year  $N$  and  $M$ .

In addition, the income projections we generated through our workflow were also used to analyse the evolution of the number of people at risk of poverty. The poverty indicator we used is the ‘at-risk-of-poverty threshold’, defined by Eurostat as the share of people below 60% of the national median disposable income in 2015 [27]. However, This threshold was not considered constant over time: it iteratively increased with the country’s income growth rate, following equation (6) (S2 figure),

$$\text{poverty\_threshold}_{t+1} = \text{poverty\_threshold}_t * g. \quad (6)$$

For 2015 (the initialisation year), the individual-level poverty threshold was translated to a pixel-level threshold before performing the poverty analysis. First, 2015 individual income distribution deciles were retrieved for each country from Eurostat data

([https://ec.europa.eu/eurostat/databrowser/view/ilc\\_di01/](https://ec.europa.eu/eurostat/databrowser/view/ilc_di01/)). Using the fifth decile (median), we calculated each country's at-risk-of-poverty threshold (60% of the median). Then, we identified which percentile corresponded to this threshold in the 2015 income distribution (individual level). For thresholds falling between two deciles, linear interpolation was used to determine the corresponding exact percentile. The pixel-level at-risk-of-poverty threshold was finally calculated by retrieving the income value corresponding to this percentile from the 2015 gridded income distribution (pixel level) [15].

### 3. Results

#### 3.1. Regressing income growth rate from GDP growth rate

The results show that the correlation between per capita income and GDP growth rates is positive and significant both at the European level and for most individual countries (S3 Table). The impact of outliers was minimised using robust linear regression, as some countries in the past exhibited very high GDP growth rates with low-income growth rates (figure 2). The obtained regression coefficients at the European level suggested that future per capita income growth rates can exceed or be below GDP growth rates. More specifically, when future annual GDP growth rates are below 2.6% (red line above the blue line), income growth rates will grow faster; the reverse will be observed for, when GDP growth rates above 2.6%. On average, our findings indicate that disposable income growth rates exceed GDP growth rates, increasing the income-to-GDP ratio across all countries and SSP between 2015 and 2100 (S3 figure). This trend aligns with recent observations from 2008 to 2019 in several OECD countries [24]. The income-to-GDP ratio remains below one in all countries, indicating that per capita GDP consistently exceeds per capita income across all SSP by the end of the century.

#### 3.2. Linking individual and pixel-level distributions of income

We found significant differences between individual and pixel-level income distributions in 2015, with income being more concentrated at the individual level. Indeed, in most countries, individuals in the top decile (d10) capture more than 25% of total income, whereas this share rarely exceeds 16% at the pixel level (figure 3). Across all countries analysed, 55% were best fitted using a logarithmic regression, while the others were fitted using a linear regression. Overall, the regression accuracies were high, with a coefficient of determination ( $R^2$ ) exceeding 0.84 in over 90% of countries. In a few countries, such as Albania, Serbia or Montenegro, the  $R^2$  ranged between 0.54 and 0.73, which can be explained by the low levels of inequality in the 2015 gridded income data in Eastern Europe

[15]. S1 Table provides country-level information on the type of regression used along the obtained  $R^2$  coefficient.

#### 3.3. Changes in per capita income distribution across the 5 SSP at the European level

At the European level, changes in per capita income distribution are primarily driven by the projected income growth rates at the national level. Across all five SSP, the spatial distribution of income in 2100 appears similar to 2015 (figure 4). This is mainly due to the convergence mechanism included in all SSP narratives (i.e. countries with lower initial income levels experience income growth that converges toward but does not surpass those of wealthier countries).

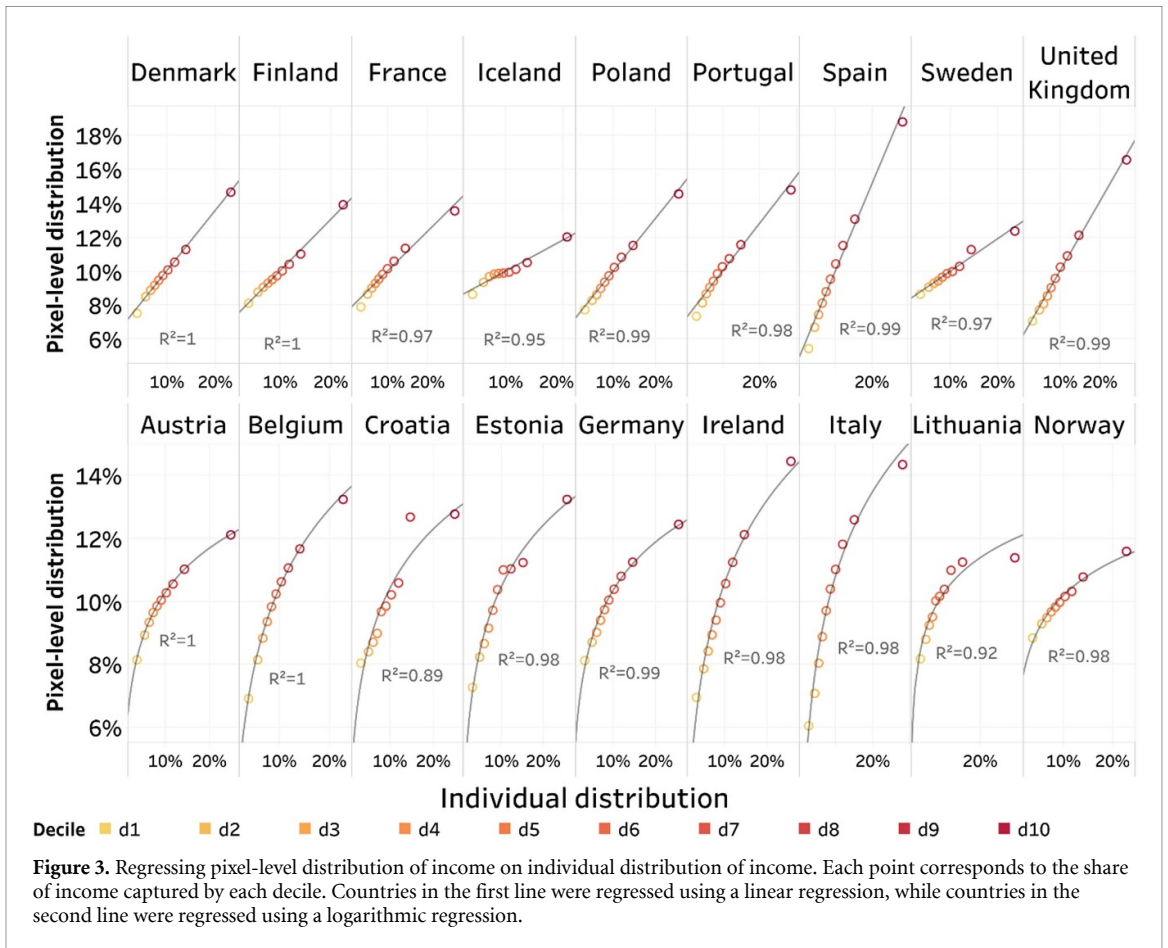
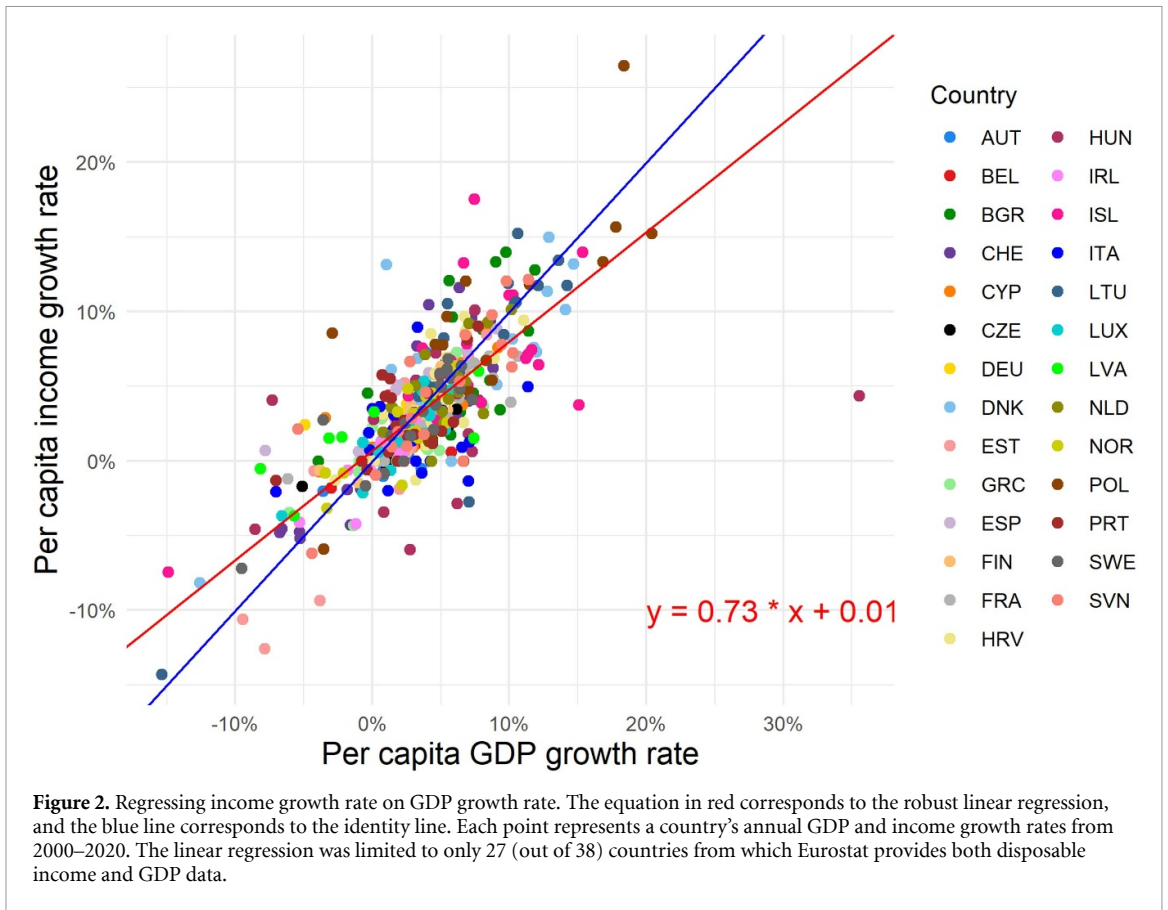
However, the use of income growth rates on per capita disposable income tends to break the convergence mechanism of the SSP partially. Indeed, since the relative position of countries in terms of per capita income and per capita GDP can differ, applying affine transformations of GDP-based convergence rates to income can lead to some countries surpassing the income levels of initially wealthier countries. For example, countries like Ireland, the United Kingdom, Cyprus, and Spain have a relatively higher income distribution ranking in 2100 across all SSP compared to 2015. In contrast, Denmark, Sweden, and Switzerland experience a relative decline, with many regions dropping from the top two quintiles to the third quintile.

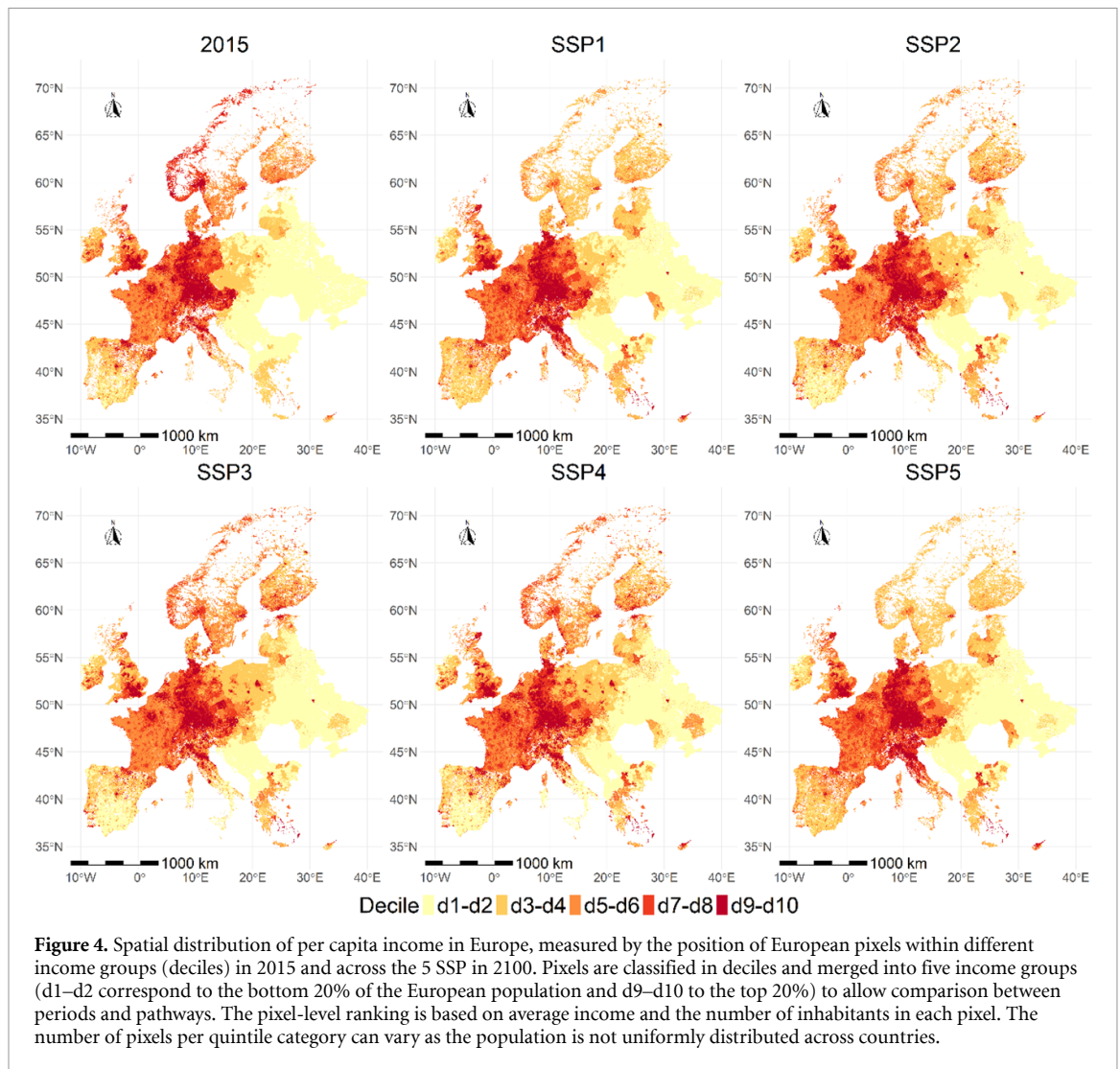
SSP1 and SSP5 show similar spatial trends, with per capita income spatial patterns essentially unchanged from 2015, except for some Balkan countries that experience an economic catch-up (figure 4). In contrast, SSP3 and SSP4 exhibit more heterogeneous changes in income patterns within countries, often intensifying pre-existing disparities. For instance, in Italy, while northern regions remain in the highest European income deciles by 2100 in all SSP, southern regions experience a more pronounced decline in SSP3 and SSP4 (most areas are in the first and second decile categories). A similar divide is seen in Germany, with a clear separation between the wealthier Western regions and the poorer Eastern regions by the end of the century. These findings are consistent when looking at per capita income evolutions in absolute terms (S4 figure).

The SSP also differ in their projections of settlement expansion. SSP1 and SSP5 show the lowest rates, with settlement areas expanding by 6.5% across Europe. SSP4 follows at 7.3%, SSP2 at 8.2%, and SSP3 shows the highest growth, adding over 8.5% to the 2015 populated areas.

#### 3.4. Application 1: shifts in income ranking

We observed varying ranking shifts across European countries in the 2015–2100 period (figure 5). In many countries, inhabitants of populated areas benefited





**Figure 4.** Spatial distribution of per capita income in Europe, measured by the position of European pixels within different income groups (deciles) in 2015 and across the 5 SSP in 2100. Pixels are classified in deciles and merged into five income groups (d1–d2 correspond to the bottom 20% of the European population and d9–d10 to the top 20%) to allow comparison between periods and pathways. The pixel-level ranking is based on average income and the number of inhabitants in each pixel. The number of pixels per quintile category can vary as the population is not uniformly distributed across countries.

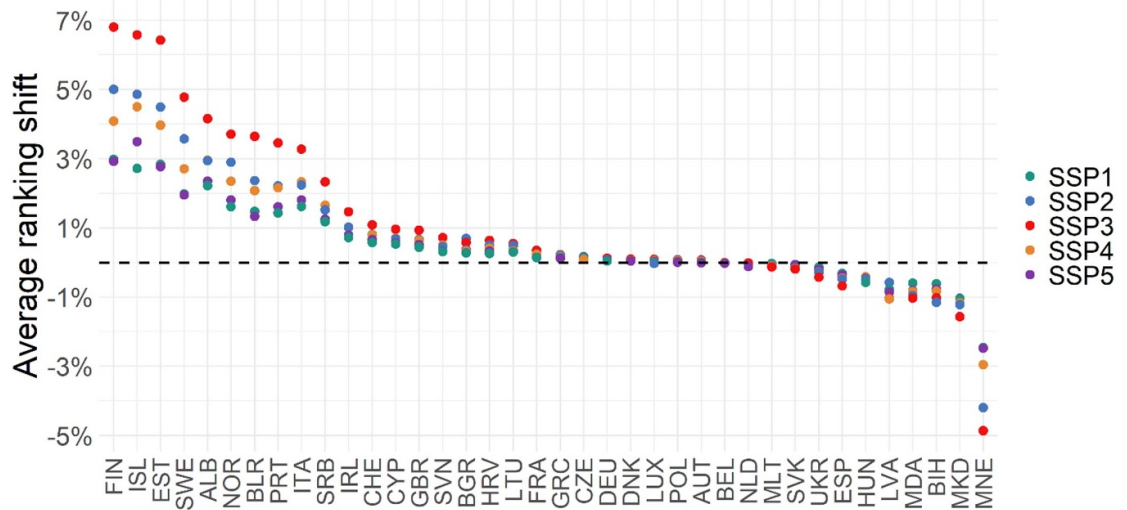
from a positive ranking shift (up to 7% in Finland), meaning that they will have a relatively higher per capita income rank in 2100 compared to 2015. In Sweden, for instance, inhabitants would gain an average ranking ranging from 2% in SSP1 to 5% in SSP3. This positive change can be explained by the localisation of new settlements, mainly next to areas belonging to the first deciles in 2015 (figure 6). As in our methodology, the average income of newly populated pixels is assessed by calculating the average income of pixels surrounding them, these pixels will probably be added at the bottom of the distribution. The addition of these low-income pixels will progressively increase the relative ranking of higher-income pixels. S2 Table provides a country-level evolution of settlement shares between 2015 and 2100 across all SSP.

Conversely, we observe negative ranking shift indexes in nine European countries, including Spain, Hungary, and Montenegro. The income distribution in Montenegro is expected to experience significant changes, with populated pixels in 2015 set to face

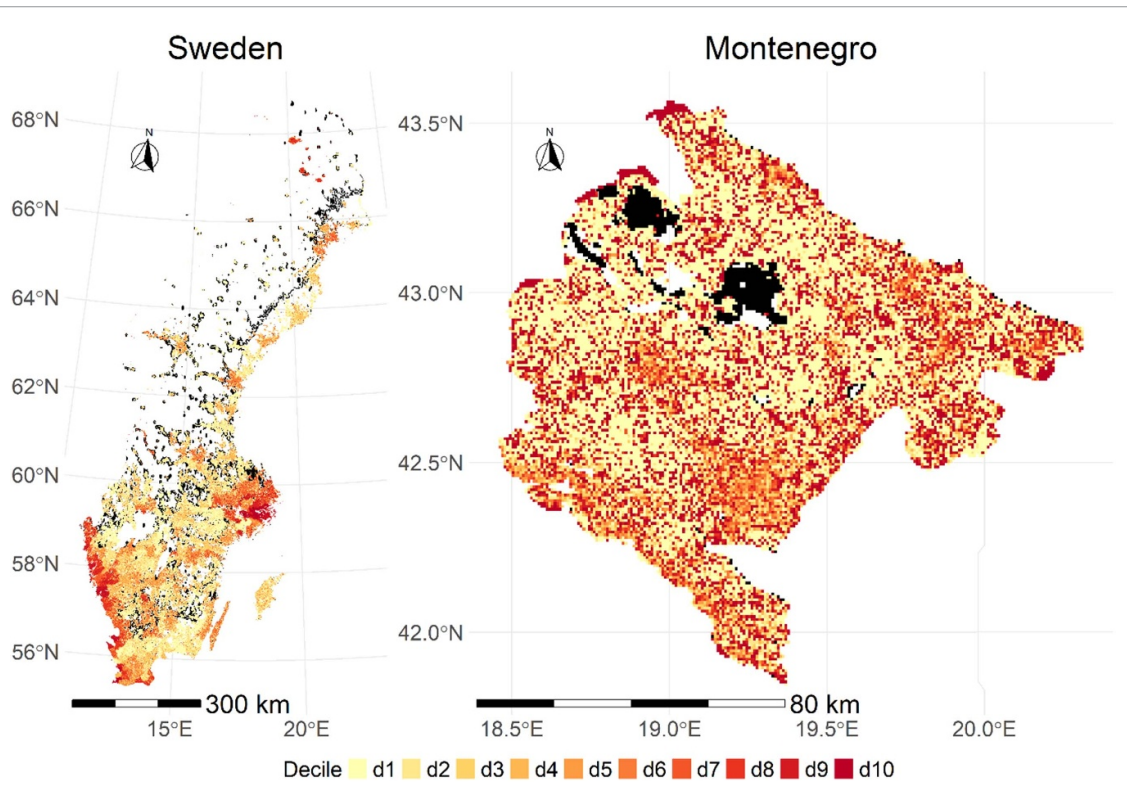
a decrease in ranking ranging from  $-5\%$  in SSP3 and  $-2\%$  in SSP1. This downward trend can partly be attributed to the localisation of new settlements next to high-decile areas (figure 5). Adding new pixels at the top of the distribution will push poorer pixels to lower ranks, hence engaging a global downward trend. Additionally, as the 2015 gridded income dataset for Montenegro has fewer income disparities compared to other countries [15], pixels have a higher chance of experiencing a ranking shift if future income maps are built by applying different decile-level growth rates.

### 3.5. Application 2: evolution of poverty across the SSP

The share of the population at risk of poverty varies significantly across countries and SSP (figure 7(a)). In Europe, this share is projected to rise from 12.5% in 2020 to over 30% by 2100 under SSP3 and SSP4. In contrast, it is expected to decline to below 10%



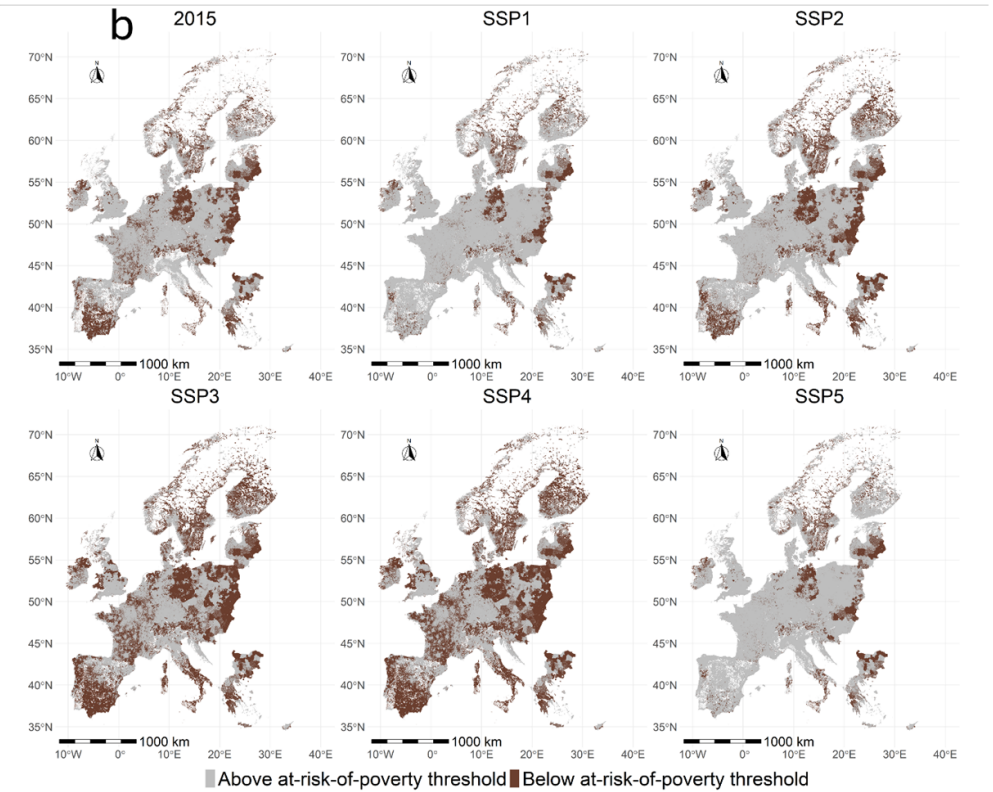
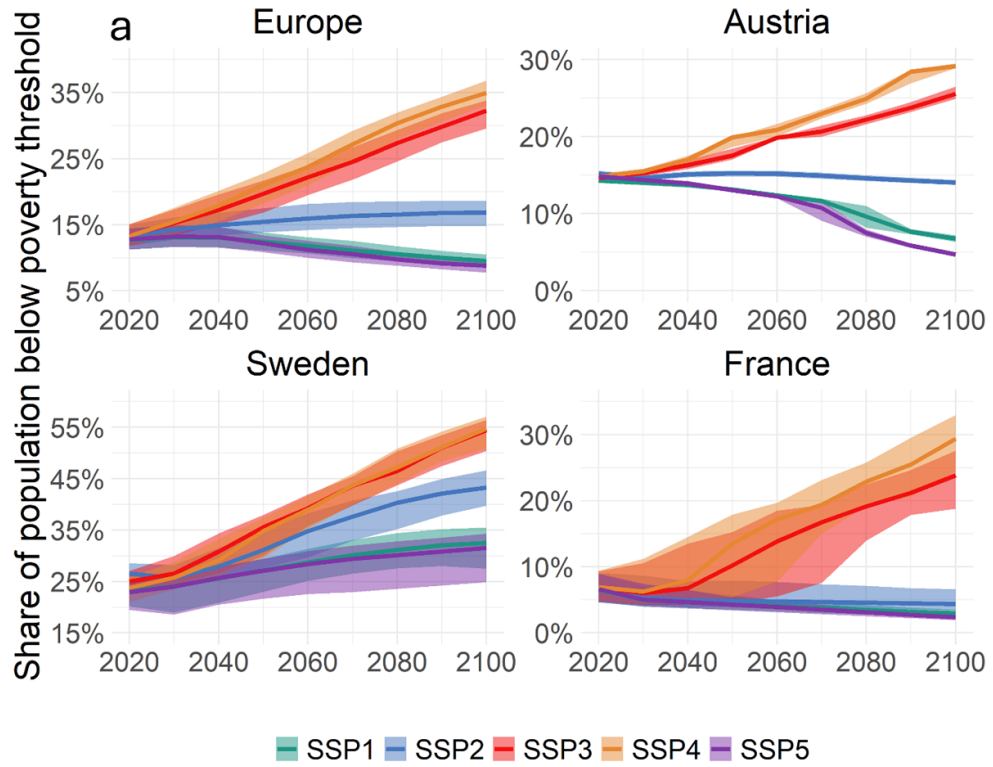
**Figure 5.** Country-level ranking shift index between 2015 and 2100 across the 5 SSP. A positive value of 1% means that populated areas in 2100 will gain, on average, a 1% ranking compared to 2015 (e.g. a pixel ranked 12 out of 100 in 2015 would be ranked 14 out of 107 in 2100 considering settlement expansion and shrinkage).



**Figure 6.** Evolution of the spatial distribution of per capita income in Sweden and Montenegro between 2015 and 2100. In both countries, we represented the decile category of each pixel in 2015 and added in black the geographical distribution of new settlements in SSP5 for Sweden and SSP3 for Montenegro. In Sweden, new settlements are mainly located next to pixels belonging to the first decile levels and next to the top deciles in Montenegro.

under SSP1 and SSP5 and to stabilise at over 15% under SSP2. As a result, the number of areas below the at-risk-of-poverty threshold is expected to increase drastically under SSP3 and SSP4 and decrease under SSP1 and SSP5 (figure 7(b)). A similar trend is observed at the country level, with half of the countries projected to have over 30% of their population

at risk of poverty under SSP3 and SSP4 by 2100 (S5 figure). However, some countries, such as Sweden, are anticipated to follow a different pattern, showing increased poverty across all SSP (figure 7). An increase (or decrease) in the total population at risk of poverty indicates that this group will experience income growth lower (or higher) than the national



**Figure 7.** Population below national at-risk-of-poverty threshold between 2020 and 2100 across the 5 SSP. (a) Share of population at-risk-of-poverty in Austria, Sweden, France, and at the continental level in Europe. In Europe, the results are based on aggregating country-level populations using national at-risk-of-poverty thresholds. The envelope represents the uncertainty analysis on the regressed parameters. (b) Evolution of European distribution of at-risk-of-poverty population. Albania, Belarus, Bosnia and Herzegovina, Malta, Moldavia, Montenegro, and North Macedonia were not included as the decile-level distribution of income needed to be provided in Eurostat data.

average, the rate at which the poverty threshold increases. These results align with the projected high economic growth and reductions in inequality

described in SSP1 and SSP5, as well as the contrasting trends of lower economic growth and persistent inequality in SSP3 and SSP4 [6, 8, 14].

## 4. Discussion and conclusion

In this study, we developed a new methodology to generate 1 km gridded decadal maps of per capita disposable income consistent with the SSP throughout the 21st century. To generate these projections, we implemented an iterative top-down approach, which mobilises existing datasets for several socioeconomic variables, such as population projections [19], GDP growth [8] and settlement expansion [31]. Because our study focused on projecting income rather than GDP, we additionally ensured consistency with existing quantitative SSP projections of future inequality [14], represented by the share of total income captured by each decile category [18].

Across the 5 SSP, the projected income maps in 2100 reveal a persisting global spatial distribution of income compared to 2015 (figure 4). This finding is primarily driven by the future country-level GDP growth rates outlined in the SSP, which assumes a convergence process (i.e. less developed countries will catch up with richer countries through higher income growth rates). However, this assumption can be questioned on several grounds. First, such assumptions are often considered overoptimistic as the high and continuous growth rates they imply contrast with past economic disruptions (e.g. economic crisis) and observed growth rates that have happened in the past [35, 36]. International sanctions, regional conflicts, and climate-induced migration for instance have the potential to generate nonlinear shocks to future economic development, potentially giving rise to new poverty hotspots, particularly in SSP3 ('regional rivalry'). Indeed, SSP3 is the scenario for which we found the highest income-to-GDP ratios at the end of the century (44%–93%, average at 75%), which requires deep transformations of the current economic system to happen in practice. It is important to note that SSP3 storyline assumes a decline in international economic cooperation, which could increase the income-to-GDP ratio by reducing the share of domestically generated income (part of GDP) that flows to non-resident households or companies. In the remaining pathways, the income-to-GDP ratio is lower in 2100 (S3 figure). Finally, as these SSP projections span an 80 year period, significant structural, economic, and geopolitical changes are likely to occur, introducing considerable uncertainty into long-term estimates.

Second, the convergence assumption preserves existing power imbalances between countries, limiting the narratives from considering shifts in geopolitical power dynamics. While protecting the status quo may seem more plausible, narratives exploring changes in power relations between European countries could provide valuable insights and foster emancipatory knowledge [37, 38]. Third, these SSP narratives are misaligned with critical climate and energy

justice aspects, particularly in how the global carbon budget is shared [39]. To address this, future projections could better account for political contexts within the SSP storylines and consider more contrasted convergence scenarios in their analysis. Scenarios based on post-growth or degrowth economic modelling [40, 41] have the potential to address these limitations.

At the country level, our methodology yielded higher income growth rates than those projected by the GDP growth rates of the SSP (S3 figure). This led us to examine how this result can influence the evolution of the distribution of income using two approaches: (1) a ranking shift indicator that tracks the evolution of the relative ranking of pixels between 2015 and 2100 and (2) an absolute poverty threshold at the country level to estimate the evolution of the population at-risk-of-poverty. Northern European countries are projected to experience notable average positive ranking shifts (ranging from 2% in SSP1 to 6% in SSP3) throughout the century, contrasting with Eastern European countries like Montenegro and Moldova, which may face a predominantly downward trend (figure 6). These trends are primarily influenced by the initial income deciles of pixels neighbouring new settlements. The integration of other existing SSP-consistent gridded population [19, 42–45] and settlement change [20, 21, 31, 46] datasets could yield alternative results, highlighting the need for harmonisation within the SSP community to enhance comparability in local climate impact research [11].

The share of the European population below the at-risk-of-poverty threshold (set at 60% of national median income) is expected to drop from 12.5% in 2015 to below 10% in SSP1 and SSP5 and to reach more than 30% under SSP3 and SSP4 (figure 7). These trends are aligned with the SSP storylines on future economic growth and inequality [6, 7, 14]. However, these findings are subject to uncertainties linked to the initial 2015 gridded income dataset. Indeed, poverty reduction is more probable when initial income disparities between pixels are low within countries. Although the 2015 gridded income dataset [15] provides the highest available resolution in Europe, it lacks spatial granularity in Eastern Europe, resulting in lower income variability for these countries. Future research efforts could encourage institutional actors to improve the measurement of local economic data and to open their access to researchers. Alternatively, developing high-resolution income maps may benefit from recent developments in remote sensing and artificial intelligence [47, 48]. These results are also influenced by the regressions performed to predict future income growth rates. In particular, applying a single relationship between disposable income and GDP growth rates across all countries might expose us to Simpson's paradox [49]. Similarly, the use of a constant relationship between

individual and pixel-level distributions over the century can be questioned. This relationship is shaped by both overall inequality and spatial disparities, which are often rooted in historical development gaps and influenced by policy interventions (e.g. social housing policies promoting social diversity in neighbourhoods). These dimensions are specific to each country and can be hard to capture in the SSP storylines. The uncertainty analysis on the regressed parameters shows alternative trends on future poverty estimates, with such parameters having a high influence on results for France and Sweden, little influence for Austria and moderate influence for the results aggregated at the European level (figure 7 panel (a)). Finally, these results can also be influenced by the resolution at which they are calculated and may differ in applications employing coarser resolutions [50].

To the best of our knowledge, we have produced in this study the first European gridded dataset of per capita disposable income consistent with the SSP up until 2100. This dataset can be used to study the link between inequality, exposure to environmental degradation, and access to environmental amenities. More importantly, considering different development pathways allows exploring how this link might evolve in the future. This dataset can be used to study the future vulnerability of individuals to climate change impacts in order to design just adaptation pathways.

### Data availability statement


Decadal disposable income maps consistent with the SSP available at the Recherche Data Gouv repository [51] under the Creative Commons BY-NC-SA 4.0 license. The replication data is available at the Recherche Data Gouv repository [52] under the Creative Commons BY-NC-SA 4.0 license. The code used to generate this data set is accessible in the Zenodo through Gitlab repository [53] under the GNU Affero General Public License v3.0.

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