

Global gridded data for the Shared Socio-economic Pathways

Oliver Perkins^{1,2,3*}, Ankita Saxena^{4*}, James D.A. Millington^{1,2}, Bumsuk Seo⁵, Calum Brown^{4,6}, and Mark Rounsevell^{4,7,8}

¹Department of Geography, Kings College London, London, UK

²Leverhulme Centre for Wildfires, Environment and Society, London, UK

³School of Environmental Sciences, University of East Anglia, Norwich, UK

⁴Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Garmisch-Partenkirchen, Germany

⁵Institute of Construction and Environmental Engineering, Seoul National University, Republic of Korea

⁶Highlands Rewilding Limited, Inverness, UK

⁷Institute for Geography & Geo-ecology, Karlsruhe Institute of Technology, Karlsruhe, Germany

⁸School of Geosciences, University of Edinburgh, Edinburgh, UK

Abstract

The shared socio-economic pathways (SSPs) provide storylines for plausible future global developments under a consistent set of assumptions. Primarily, the SSPs have been used to derive quantitative scenarios of greenhouse gas emissions for use in general circulation models and other large-scale, physically based models of environmental change. Their use in large-scale socio-environmental simulation modelling has been less forthcoming. Behavioural models of land systems, typically operating within agent-based frameworks, attempt to explicitly represent the varied socio-environmental factors that characterise the SSP storylines. Such simulation models are often geospatial and grid-based, capable of representing dynamics at resolutions of up to 10s km² over large extents (continental to global). However, such approaches demand geospatial (usually gridded) input data for multiple social and human variables - often together known as capitals - such as education levels and infrastructure. The lack of such input data for the future SSP storylines has been a substantial limitation in the application of large-scale behavioural models of land systems specifically and of socio-environmental modelling more generally. Here, we present global gridded data for socio-economic capitals useful for simulation models and consistent with the SSP storylines, disaggregated spatially to a 0.25° grid. We analyse the spatial and temporal characteristics of the projected data, comparing them to projections of GDP, and discuss their utility and limitations for large-scale socio-environmental modelling.

Keywords

data; humans; shared socio-economic pathways; global

Data availability

All data presented in this study are made freely available at: <https://doi.org/10.5281/zenodo.14178581>.

1. Introduction

The shared socio-economic pathways (SSPs) are widely used to complement the representative concentration pathway (RCP) emissions trajectories, providing storylines for plausible future global developments under a consistent set of assumptions (O'Neill et al., 2014). These storylines describe trends in socio-economic development and so determine a wide range of the human dimensions of modelled scenarios, including possible

Correspondence:

Contact O. Perkins at oliver.perkins@kcl.ac.uk

*These authors contributed equally

Cite this article as:

Perkins, O., Saxena, A., Millington, J.D.A., Seo, B., Brown, C., & Rounsevell, M.

Global gridded data for the Shared Socio-economic Pathways

Socio-Environmental Systems Modelling, vol. 8, 18850, 2026, doi:10.18174/sesmo.18850

This work is licensed under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/).



Socio-Environmental Systems Modelling

An Open-Access Scholarly Journal

<http://www.sesmo.org>

future climate mitigation and adaptation (O'Neill et al., 2017; Table 1). Studies show that these socio-economic conditions can be just as important as climate for numerous socio-environmental systems including food production (Popp et al., 2017), biodiversity (Newbold et al., 2015) and resilience to natural hazards (Botzen et al., 2019; Panwar & Sen, 2019).

Table 1: Key aspects of the shared socioeconomic pathways (SSPs) for the data projections presented in this study based on O'Neill et al. (2017). Energy intensity gives the energy consumed per unit of economic production, not absolute energy consumption. This study's indicators are given in the brackets, and are shaped by the SSP dimension. LIC, MIC, HIC = Low-, Middle- and Higher-income countries.

Dimension	SSP1: Sustainability	SSP2: Middle of the road	SSP3: Regional rivalry	SSP4: Inequality	SSP5: Fossil-fuelled development
Economic growth (GDP, Market access, energy consumption)	LIC/MIC: High HIC: Medium	Medium	Slow	LIC: Low MIC/HIC: High	High
Population growth (Working age pop., market access, energy consumption)	Relatively low	Medium	High	Unequal	Relatively low
Urbanisation (Market access)	High; well-managed	Medium	Low; poorly managed	High; mixed across cities	High; sprawl
Energy intensity (Energy consumption)	Low	Uneven, higher in LIC	High	Low/medium	High
Inequality (Gini, Education, Health)	Reduced	Uneven, moderate reductions	High, especially across countries	High, especially within countries	Strongly reduced
Education (Education)	High	Medium	Low	LIC: Low HIC: Medium	High
Health spending (Health)	High	Medium	Low	LIC: Low HIC: Medium	High

However, most analyses (especially quantitative and model-based) use only a fraction of the detail available in the SSPs, focusing scenarios on a very limited number of factors and often collapsing the SSP storylines to projections of GDP and human population density (Koch & Leimbach, 2023; O'Neill et al., 2020). This was true even for the Intersectoral Impacts Model Intercomparison Project (ISIMIP), which seeks to understand the human impacts of environmental change (Frieler et al., 2024). Such a focus is challenging given that GDP and population density will not always represent the main drivers of change, and their impacts could be confounded by other, unmodelled drivers.

For example, models in the Fire model intercomparison project (FIREMIP; Rabin et al., 2017) represented human impacts on global burned area through population density and GDP alone, using relatively simple quantitative relationships. Results were variable and inconclusive, with models unable to agree on whether human activity would increase or decrease global burned area over the coming century (Teckentrup et al., 2019). The narrow focus on GDP and population density likely arises, at least in part, because of a lack of capability in established models (including many integrated assessment models) to handle social factors, perhaps as well as assumptions that economic productivity and sheer numbers of people alone determine outcomes (Ackerman et al., 2009).

Yet many socio-environmental models do not rely on simple assumptions of money and mass, aiming instead to represent the importance and impacts of human agency and socio-cultural attributes on environmental change. For example, Competition for Resources between Agent Functional Types (CRAFTY; Murray-Rust et al., 2014), a large-scale behavioral modelling framework has been widely used to model land use and management over national to continental extents (Brown et al., 2021, 2022; Millington et al., 2021), representing drivers including social-influence networks, policy change and non-monetary values. Similarly, the WHAM! model was developed to improve representation of human impacts on fire regimes in dynamic global vegetation models (Perkins et al., 2024), capturing how syndromes of human fire use and management emerge from the interplay of social

and environmental factors (Perkins et al., 2025a). Such simulation models are geospatial and grid-based, capable of representing dynamics at resolutions of up to 10s km² over large extents (regional to global), requiring corresponding input data. They also rely on the notion of different types of social and economic capital that represent heterogeneity of resources across space, and influence competition between simulated agents to occupy that space (Arneth et al., 2014; Perkins et al., 2022).

Types of capital span ‘financial capital’ (the economic context of a location), ‘human capital’ of individuals (such as education and skills), ‘social capital’ of interactions between individuals in a location (including governance structures and institutions), and ‘infrastructure capital’ representing accessibility of a location for resource extraction (including transport networks and supply chains) and energy consumption. Developing geospatial gridded capitals from empirical data can require assumptions about process (e.g. the influence of road surface on travel times, (de Castro Victoria et al., 2021), or rely on more straight-forward re-classification of existing empirical datasets (e.g. land cover, Blanco et al., 2017). However, to-date projections into the future for such models have relied on abstract ‘scenarios’ that simply use proportional change in the capitals (e.g. Millington et al., 2021), primarily because future projections of capitals based on existing data have been limited.

Recognising the importance of measures beyond population density and GDP, several projections of other dimensions of human futures have been made – typically aggregated for countries or larger global regions. For example, Rao et al. (2019) provide country-level SSP projections of the Gini inequality index, whilst Meijer et al. (2018) project road density also at country-level. In addition, Integrated Assessment Models (IAMs) provide outputs for global regions, including for energy consumption, which, together with emissions pathways and GDP projections, can provide an important indicator of how far economic activity has been decoupled from carbon emissions (Schandl et al., 2016). However, finer spatial-scale projections (i.e. sub-national) are currently restricted to GDP (e.g. Murakami et al., 2021) and population density (e.g. Jones & O’Neill, 2016).

Here, we present global 0.25° gridded data representing the SSP storylines decadal until 2100 for a range of capitals. In doing so, we aim to characterise the SSP storylines quantitatively in ways that provide insight and enable socio-environmental and behavioural simulation modelling to explore a wider range of scenario conditions than GDP and population density alone. We describe the construction of the capital datasets based on existing projections and other assumptions and compare the outputs to existing projections of GDP. The analysis of capitals across time between the SSPs and at different levels of spatial aggregation (globally, regionally, pixel-level) allows us to highlight the strengths and weaknesses of the data for future modelling studies. The discussion (Section 4) focuses on evaluating how well these projections capture a representative range of possible futures, in addition to the implications of the reliance of the data on underlying projections at a coarse spatial resolution.

2. Methods

2.1 Overview

The spatial projections presented in this study were made of socio-economic capitals relevant to large-scale behavioural models of socio-environmental systems. Capitals were selected covering a broad range of aspects of human activity: an education index, a health index, and working age population (human capitals); the Gini coefficient (i.e. income inequality; a mixed financial and social capital); and market access and total energy consumption (infrastructure capitals). These capitals have been adopted in the WHAM! and CRAFTY agent-based models (Perkins et al., 2025b; Saxena et al., 2026), as well as statistical (Rouhette et al., 2026) and process-based biophysical models (Billing et al., 2026), and hence have already been found to add value to socio-environmental simulation modelling.

We build on existing national- and sub-national-level projections and outputs to produce gridded projections at a consistent spatial resolution of 0.25° (Table 2). We choose 0.25° as the highest resolution that could be consistently adopted across indicators. Market access, for example, relies on the LUH2 urban fraction projection which is provided at 0.25° (Hurtt et al., 2020). Similarly, the projections of education and health are based on down-scaling of shapefiles at the sub-national region level. The respective source data and output units are given in Table 2. Sections 2.2-2.4 describe the construction of the gridded socio-economic capitals, then Section 2.5 describes the methods used to analyse the data. All data presented in this paper are made publicly available at: <https://doi.org/10.5281/zenodo.14178581>. All data are provided at 0.25°, and also at higher 1km² resolution where this was warranted, given the resolution of input data sets. Data processing, including spatial projection and rescaling was conducted using the Terra package for the R programming language (v1.8; Hijmans 2025).

Table 2: Overview of gridded socio-economic capitals produced and presented. All data are provided at 0.25° resolution; * denotes data also provided at 1km² resolution.

<i>Capital</i>	<i>Input Data (Baseline)</i>	<i>Input Data (Projection)</i>	<i>Rescaling Method</i>	<i>Output units</i>
<i>Health</i>	HDI health index (Kummu et al., 2018)	Life Expectancy (UNDESA, 2022) Country-level Gini (Rao et al., 2019)	Rasterisation of sub-national polygons	0-1 index
<i>Education</i>	HDI education index (Kummu et al., 2018)	Participation proportion (KC & Lutz, 2017) Participation years (Potančoková et al., 2014) Country-level Gini (Rao et al., 2019)	Rasterisation of sub-national polygons	0-1 index
<i>Working age population*</i>	Working Age Population (KC & Lutz, 2017) Total Population (CIESIN NASA, 2018)	Working Age Population (KC & Lutz, 2017) Total Population (Jones & O'Neill, 2016)	Rasterisation of national data using population	Persons per km ⁻²
<i>Gini*</i>	Country-level Gini (Rao et al., 2019) 'Light Gini' index (Mirza et al., 2021)	Country-level Gini (Rao et al., 2019)	Rasterisation of national data using 'light Gini'	0-1 index
<i>Total energy consumption*</i>	Energy use per capita (EIA 2024, EI 2024)	Energy supply (Riahi et al., 2017, Bauer et al., 2017) Total Population (Jones and O'Neill 2016)	Rasterisation of national data using population	kWh
<i>Market access</i>	Urban Fraction (Hurtt et al., 2020) Population Density (CIESIN, 2017) Road Density (Meijer et al., 2018) GDP per capita (Kummu et al., 2018) Distance to ocean (NASA, 2009)	Urban Fraction (Hurtt et al., 2020) Total Population (Jones & O'Neill, 2016) Road Density (Meijer et al., 2018) GDP per capita (Murakami et al., 2021) Distance to ocean (NASA, 2009)	None	0-1 index

2.2 Human Capitals

2.2.1 Health and Education

The human development index (HDI) comprises three indices – ‘a long and healthy life’ (the ‘health’ component), ‘access to education’ (the ‘education’ component), and ‘a decent standard of living’ (the ‘economic’ component; UNDP, 2024). Each component index ranges 0-1 and the HDI is then calculated as the geometric mean of the three components. Here we present data for the health and education indices that could later be combined with an economic component to create the HDI. Projections of the health and education indices were computed in two stages. First, national-level projections were made for each country under each SSP from 2010-2100 Section 2.2.1.1). Second, these national-level projections were downscaled to the sub-country units used by Kummu et al. (2018) – for example USA or Brazilian States (Section 2.2.1.2). The resulting polygon-based maps were rasterised to the target resolution (0.25°).

2.2.1.1 National-level projections

The health index is based on life expectancy. National-level life expectancy data were sourced from the United Nations Department of Economic and Social Affairs (UNDESA, 2022). These are presented as a baseline, ‘high’ and ‘low’ scenario. The SSP narratives of O’Neill et al., (2017) describe SSP1 and 5 as having ‘high’ health investments, SSP2 as having ‘medium’ health investments and SSP3 and 4 as having ‘low’ health investments. Therefore, the UN baseline scenario was interpreted as reflecting SSP2, the ‘low’ scenario as reflecting SSPs 3 and 4, and the ‘high’ scenario as SSPs 1 and 5. These projections were then used to calculate the health index at national level using min-max normalisation, with a minimum value of 20 years and a maximum value of 85 (following the standard UN HDI methodology; UNDP 2025).

The education index in HDI comprises two elements: mean years of schooling (years of education participation in the adult population) and expected years of schooling (based on participation rates at any given scenario year). We use the same method, but the basis of our national-level education index is the projections of education participation of KC and Lutz (2017). The HDI education index is based on years of schooling, but KC and Lutz give fractions of the adult population with primary, secondary and tertiary education (for both elements). To convert these national population fractions into estimated years of schooling per person we multiplied them by the global estimate of mean years per stage of education presented by Potančoková et al. (2010).

However, these global estimates mask substantial variation by country. To account for this, we use linear bias correction, modelling national predictions against historical data for 2019 (the most recent year with historical data available). For the education index, biases were different across global regions (ANOVA, $p < 2.2e^{-16}$), and therefore each sub-national unit’s World Bank Region was used as a categorical predictor variable. After this bias correction, the predictions of the education index achieved $r^2 = 0.850$ for 2019 (Figure 1). For the health index there were very slight differences between historical data and calculations based on future projections (with little bias between regions), and after bias correction predictions achieved $r^2 = 0.997$ for 2019.

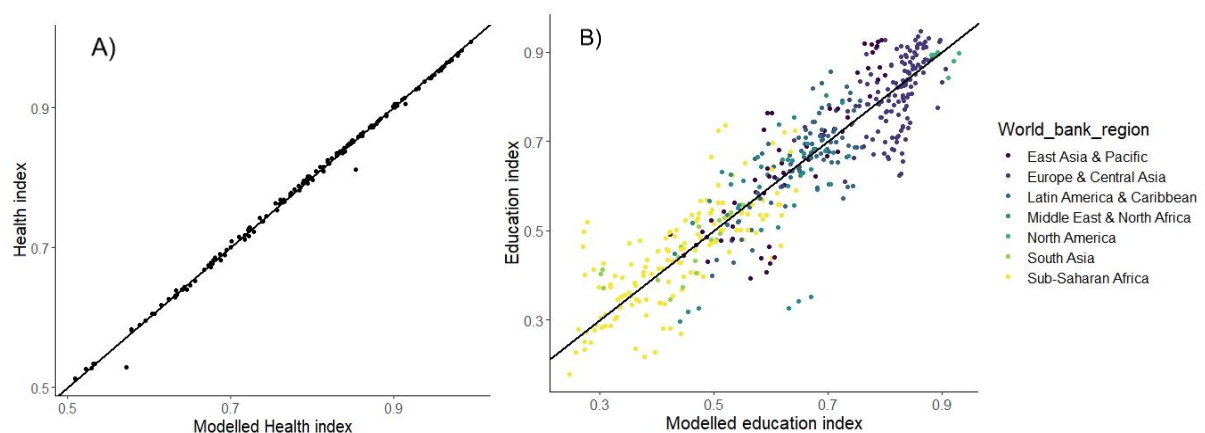


Figure 1: Linear bias correction of modelled HDI indices A) health, B) education) against historical data for 2019. The health index is reproduced almost exactly ($r^2 = 0.997$). The education index has more uncertainty, though historical data is still reproduced effectively ($r^2 = 0.850$).

2.2.1.2 Sub-national projections

Sub-national downscaling of projections for health and education indices was conducted via a down-scaling factor, calculated as the ratio of the national-level index to the sub-national unit in historical data. The value in 2010 was taken as a baseline and then adjusted for each scenario year using the SSP Gini coefficient projections of Rao et al. (2019). A fractional decrease in the Gini inequality coefficient in a given country results in a proportional fractional decrease in inequality in the sub-national distribution of an index, and vice versa. Therefore, for sub-national unit l , in country c , for index k , in scenario s at year t , the downscaling factor is:

$$DF_{l,k,s,t} = DF_{l,k,s,t-1} + \left((DF_{l,k,s,t-1} - 1) \times \frac{Gini_{c,s,t} - Gini_{c,s,t-1}}{Gini_{c,s,t-1}} \right) \quad (1)$$

where DF is the downscaling factor, and $Gini$ the country-level Gini coefficient value. These downscaling factors are then multiplied by the national-level projection to give a sub-national level projection of the health and education indices. Finally, the sub-national estimates were rasterised to the target resolution (0.25°), taking the mean value where multiple polygons occupied a given pixel.

2.2.2 Working age population

For the working age population (ages 15 to 64), we used IIASA national-level population projections by age (KC & Lutz, 2017) combined with gridded total population data (Jones & O'Neill 2016). The working age population for a given location (i, j) in year t is calculated as:

$$Wpop_{i,j,t} = Tpop_{i,j,t} \times (Wpop_{c,t} / Tpop_{c,t}) \quad (2)$$

where $Wpop$ represents the working age population, $Tpop$ represents the total population and c denotes the given country. Bilinear resampling was then applied to produce the 0.25° gridded data.

2.3 Financial and social capital

2.3.1 Gini coefficient

To account for income inequality, we utilised IIASA's national level global Gini coefficient projections (Rao et al., 2019). Initially, these projections were rescaled to a finer spatial resolution of 1km using the 'light Gini' index which was calculated by Mirza et al. (2021) based on nighttime light per capita data for the year 2010. Nighttime light data was used as a proxy for economic activity, with brightness values ranging from 0 to 1. The method as described in Eq (3) was used to calculate the Gini coefficient. For each 1km pixel at location (i, j) in year t , the Gini coefficient was calculated using the following equation:

$$Gini_{i,j,t} = Gini_{i,j,2010} \times (Gini_{c,t} / Gini_{c,2010}) \quad (3)$$

where, $Gini_{i,j,t}$ is the Gini coefficient at 1km grid location (i, j) for the year t , $Gini_{i,j,2010}$ is the light Gini for the same location in 2010, and $Gini_{c,t} / Gini_{c,2010}$ is the ratio between Gini for country c in year t over year 2010. Following this, bilinear resampling was applied to aggregate the data to a 0.25° spatial resolution for compatibility with other datasets generated in the study.

2.4 Infrastructure Capitals

2.4.1 Market access

The primary existing historical global market access data (Verburg et al., 2011) were constructed by calculating the travel time to the nearest city or port for each pixel on a 1km^2 grid. Replicating this calculation for the future would not only require projections of city locations and sizes, but also of ports. Given that these have not been constructed, and their future distribution is hugely uncertain under climate change (Mahmoud et al., 2024), a simpler alternate approach was adopted. A random forest regression was trained on the Verburg et al. (2011) data (resampled to 0.25°) as the dependent variable with four independent variables that can be projected for the SSPs (as in Table 2). In addition, distance to the coastline was used as a static surrogate for ports. The random forest model was fit using the 'ranger' R-library (Wright & Ziegler, 2017), with five-fold cross-validation and a

minimum node size of 10 (achieving $r^2 = 0.74$; Figure 2). Coefficients for this random forest model were then used to estimate future market access for the SSPs using projections of the independent variables at 0.25° (Table 2).

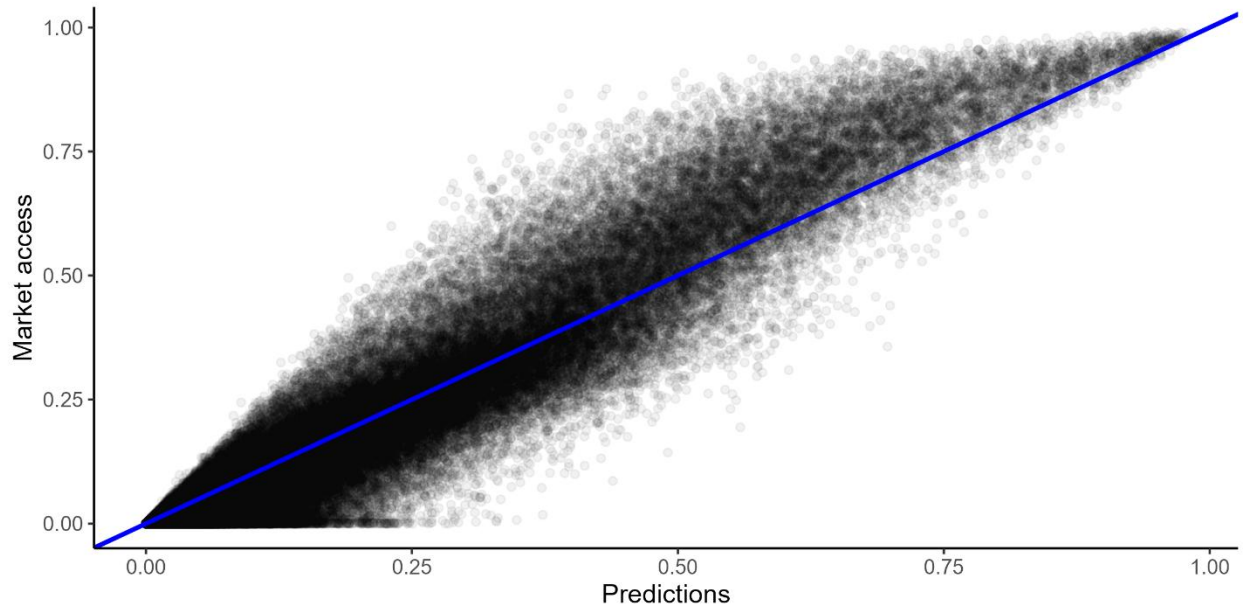


Figure 2: Predicted market access against the data of Verburg et al. (2011). Model r^2 was 0.74, with a slight tendency to under-predict market access at observed values ≥ 0.5 .

2.4.2 Energy supply

We used regional-level integrated assessment model (IAM) energy projections out to 2100 aligned with the SSPs (Riahi et al., 2017). These projections encompass various energy sources including gas, geothermal, heat, hydrogen, liquids, solar and coal and are driven by key factors such as demographic trends (population), economic development (GDP/PPP), urbanisation, energy consumption patterns, policy frameworks and technological advances (Bauer et al., 2017; Riahi et al., 2017).

Energy demand projections for the IAM regions (OECD, Reforming Economies, Asia, Middle East and Africa, Latin America) were first downscaled to the national level and subsequently to a spatial grid with a 0.25° resolution. In the initial downscaling step, energy consumption per capita (kWh) for the year 2020 was used as a baseline (Ritchie et al., 2023), applying linear downscaling to each country's projected energy consumption. The annual growth in energy consumption for individual countries was assumed to match the regional growth rate of its corresponding OECD region (eq. 4). This method is mathematically equivalent to keeping the fractional share of each country's energy consumption relative to the regional energy consumption constant, at the base year value, for the duration of the forecast period (Gaffin et al., 2004).

The bi-decadal logarithmic rate of change in energy consumption, roc , for a region r is given by:

$$roc_{r,t} = \frac{\log_e \frac{ed_{(r,t)}}{ed_{(r,t-5)}}}{5} \quad (4)$$

where ed is energy demand and t is the year. Consequently, energy consumption per capita, $PCec$, for country c within a given region r is given by:

$$PCec_{c,t} = PCec_{c,t-5} \times \exp(roc_r \cdot 5) \quad (5)$$

In turn, total energy consumption, Tec , at grid location (i, j) for year t is given by:

$$Tec_{i,j,t} = PCec_{c,t} \times Tpop_{i,j,t} \quad (6)$$

where, $Tpop_{i,j,t}$ is the total population at grid location (i, j) for the year t . Bilinear resampling was then applied to produce the 0.25° gridded data.

2.5 Data analysis

We analysed the 0.25° gridded data produced using the methods described above to: i) identify and describe patterns in the data; and ii) assess how far these capital projections explore a diversity of future scenario spaces. As noted above, where appropriate, we also include data at finer spatial resolution. Specifically, we also enclose projections of the Gini coefficient, Total Energy Supply and Working Age Population at 1km^2 . We present a comparison of these data with the harmonized projections at 0.25° in Supplementary Material 1.

Patterns in the data were identified and described in three ways, at global, regional and pixel levels. First, simple global arithmetic mean values were calculated for each capital for each SSP, as well as standard deviation, mean absolute deviation, interquartile ranges and skewness. To assess patterns of change across indicators, global means for each subsequent decade were compared to their 2020 value, and the proportional change calculated. The relative (i.e. positive or negative) and absolute (strictly positive) change from baseline was summed across capitals to establish the overall extent of change in each scenario. Second, at a regional level, the same descriptive statistical measures calculated globally were calculated for pixels grouped by the World Bank Regions (WBR; World Bank 2017), as well as the proportional change between 2020 and 2100. Third, to synthesise the large number of data points across capitals at pixel-level, the range between the maximum and minimum value for each capital was calculated across the SSPs in 2100. The resulting pixel-level ranges for total energy consumption and working age population (i.e. those capitals not already a dimensionless index) were scaled to 0-1 by dividing by the 2100 maximum value respectively. The arithmetic mean of the scaled ranges per capital was then taken. The resulting spatial maps therefore provided an 'SSP-variation index': an indicator of how divergent (or similar) a given pixel's outcomes are under the SSPs.

The assessment of how far these socio-economic capitals explore a diversity of future scenario spaces was conducted in two ways. Firstly, the summary statistics calculated for each of the socio-economic capitals (i.e. arithmetic mean, standard deviation etc.) were also calculated for the gridded GDP data of Murakami et al. (2021). This allowed assessment of how far the capitals add new information to the SSP storylines. Secondly, the scaled ranges for the six capitals (the 'SSP-variation index') were used as the basis of k-means clustering. Given the correlations between indices, data reduction was conducted using principal component analysis. So that all variables featured to some extent in the resulting cluster analysis, all six principal components (i.e. one per variable) were retained. The 'elbow method' was used to choose an appropriate number of clusters (Thorndike, 1953). This allowed assessment of how far trajectories through the SSPs varied between pixels.

3. Results

3.1 Global

Across the six socio-economic capitals, SSP5 diverges most strongly from the present in absolute terms, whilst in relative terms, SSP3 diverges most (Figure 3). Summed across capitals, by 2100 the absolute proportional change from 2020 values is 3.28 in SSP5, whilst relative proportional change in SSP3 is 2.58. There is similar tension between measures of change in the most convergent scenarios with the present. In absolute terms, the proportional divergence across socio-economic capitals is only 1.86 from 2020 baseline values in SSP4, whilst in relative terms, SSP1 apparently converges close to 2020 values (relative proportional change of 1.38). Above all, this highlights that for these socio-economic capitals, more is not always better. For example, large increases in working age population are most associated with SSP3, which has great challenges for both climate adaptation and mitigation (O'Neill et al., 2014; see section 3.2).

In comparison with human capitals, GDP changes more substantially and more uniformly. In 2100, mean proportional change across the SSPs is 4.40 for GDP, and only 2.54 for the sum of absolute change in the six socio-economic capitals we have produced. Moreover, GDP increases in all scenarios, whereas our socio-economic capitals have more varied trajectories in relative terms and can both increase and decrease. A time series of global means of each socio-economic capital by scenario is presented in Supplementary Material 1.1.

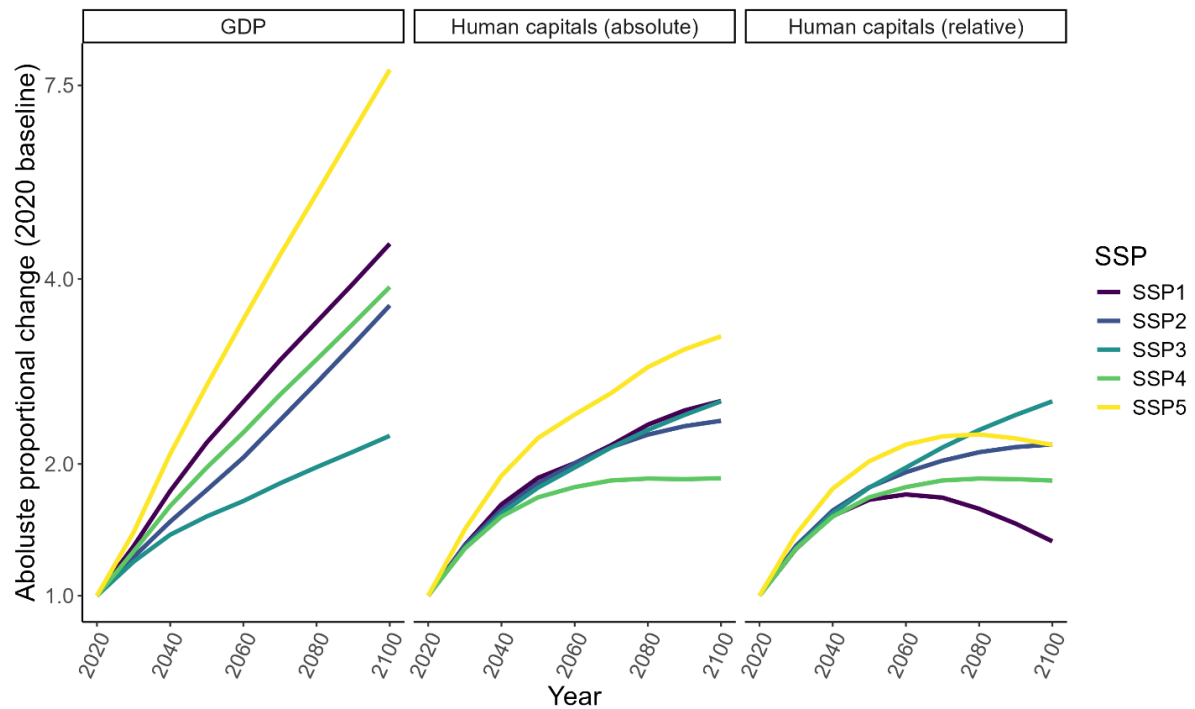


Figure 3: Proportional change across six socio-economic capitals in comparison with the gridded GDP projections of Murakami et al. (2021). Note the non-linear y-axis to capture the different scale of projected change between GDP and other capitals.

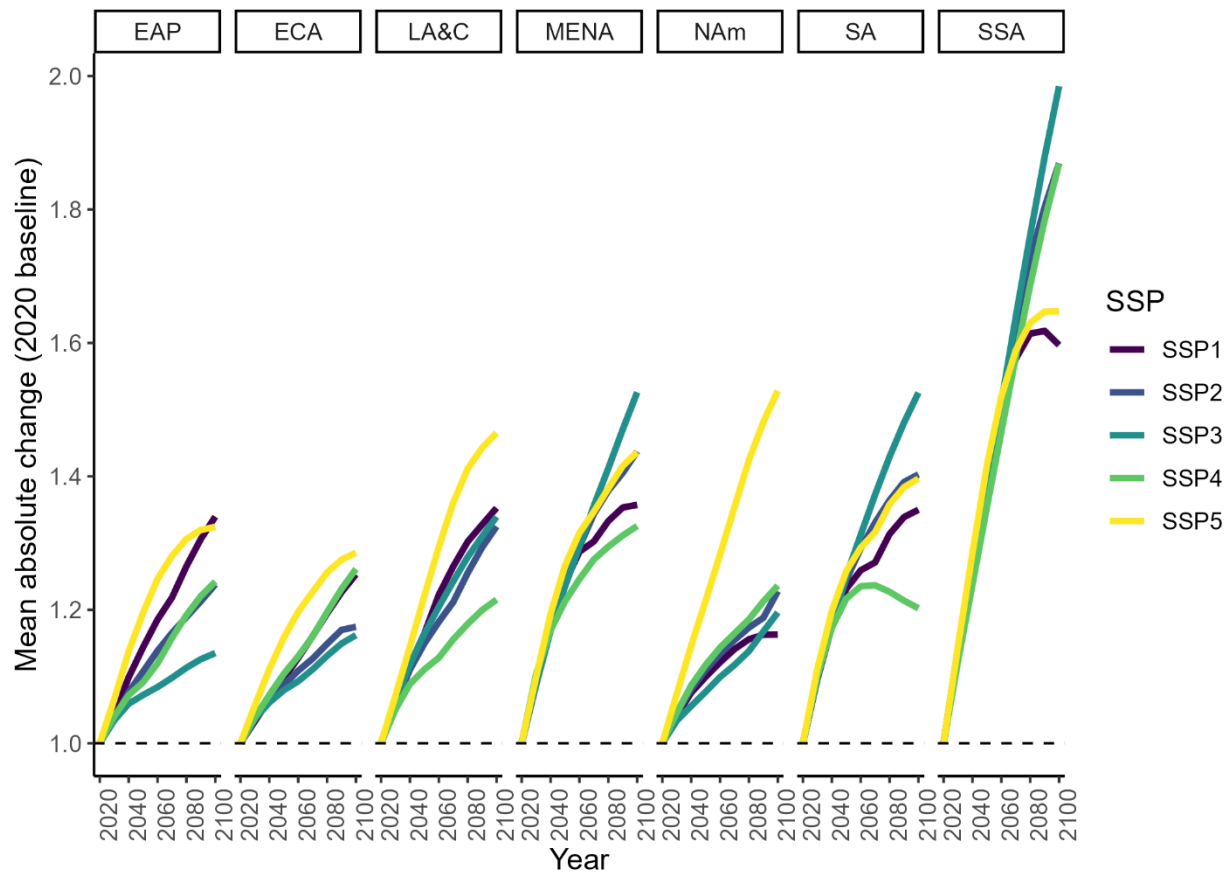


Figure 4: Time series of mean absolute change in socio-economic capitals by World Bank Region from a 2020 baseline. Change is largest in Sub-Saharan Africa (SSA), with only SSP5 in North America achieving a similar proportional change due to greatly expanded energy consumption. Conversely, SSP3 has the largest change in both MENA and SA due to a large increase in working age population. Key: EAP = East Asia & Pacific; ECA = Europe & Central Asia; LA&C = Latin America & Caribbean; MENA = Middle East & North Africa; NA = North America; SA = South Asia; SSA = Sub-Saharan Africa.

3.2 Regional

Grouping pixels regionally, change in SSPs1-4 between 2020 and 2100 is most pronounced for Sub-Saharan Africa (Figure 4). Across SSPs 1-4, indicators increase by a mean of 83% in Sub-Saharan-Africa, compared to 29% in the other world regions. However, in SSP5, North America (53%) has a similar increase to Sub-Saharan Africa (65%). The reasons for this pattern can be seen by breaking down change by capital (Figure 5). Specifically, in SSP5, total energy consumption booms in North America (+160%), whilst in other scenarios remains flat (+20%). These very large energy consumption gains in North America in SSP5 reflect well-documented concerns about the plausibility of the RCP8.5 emissions' trajectory (Hausfather & Peters, 2020). Furthermore, the reason for the comparatively modest change in Sub-Saharan Africa is due to lower growth in working age population in SSP5 (+47%) compared to SSPs 1-4 (mean +197%). Overall, this reflects the sensitivity of projections to Sub-Saharan Africa – where different development trajectories can lead to divergent outcomes.

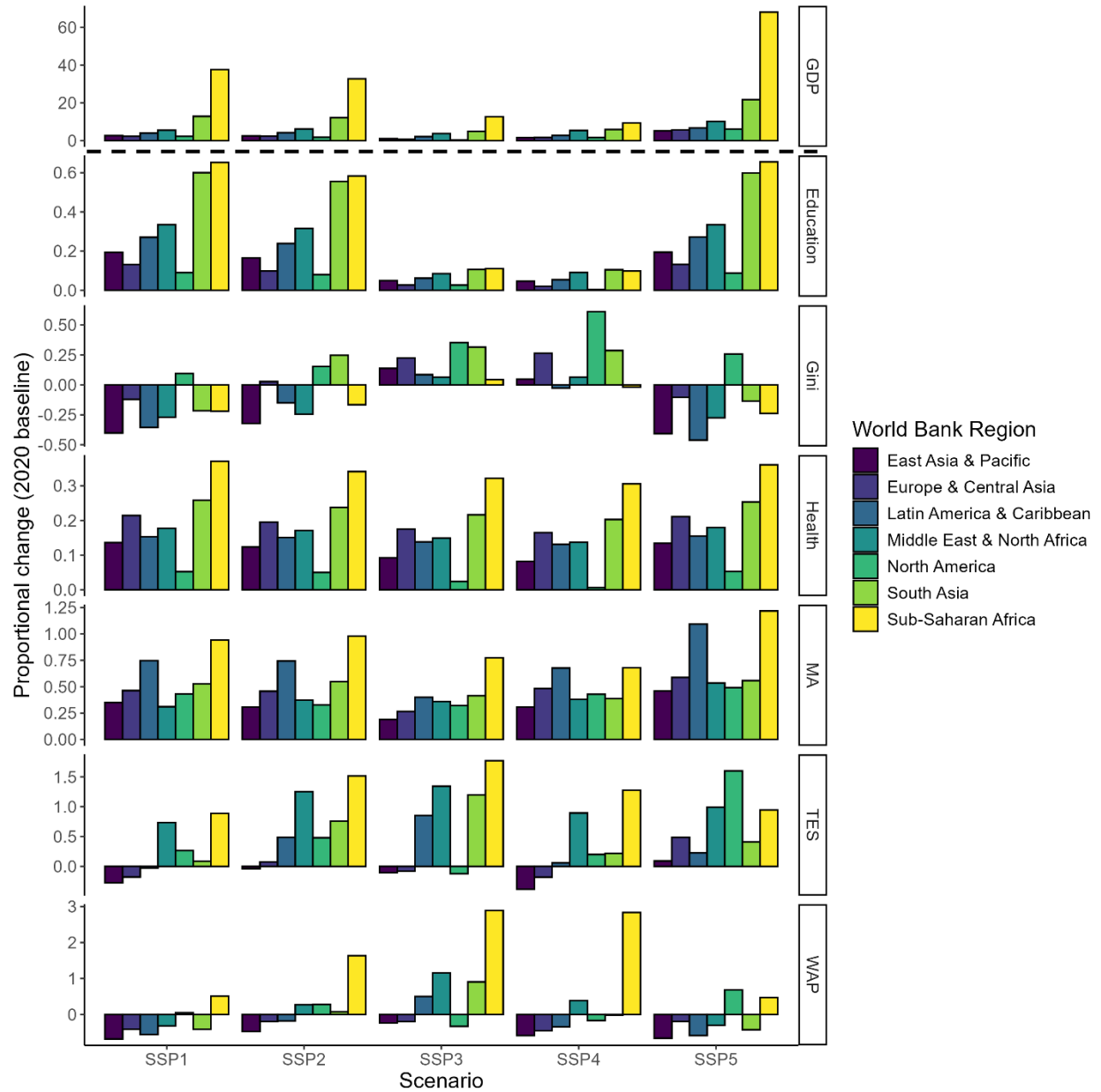


Figure 5: Change in socio-economic capitals by 2100 as a proportion of 2020 value for the World Bank regions. GDP projections of Murakami et al. (2021) are provided for comparison. Changes in GDP are an order or magnitude greater than those for all other variables. Key: MA = market access, WAP = working age population, TES = total energy supply.

By contrast, the East Asia and Pacific region (which encompasses China) has least change across all indicators. Indeed, in SSP1 and SSP4 the region exhibits an overall decline in indicators. This is due to reduced energy consumption and a decline in working age population in SSPs 1 and 4 as well as a decline in the Gini-coefficient (i.e. countries become more equal) in SSP1. Proportional change in GDP is similarly weighted towards Sub-Saharan Africa, but the amplitude of change is more extreme - reaching as much as 6798% in SSP5. A set of time series global means of each socio-economic capital by scenario and World Bank Region is presented in Supplementary Material 1.2.

In part, the comparatively rapid change in sub-Saharan Africa is due to indicator saturation in higher-income regions. For example, the health index saturates (at 1.0) when 100% of the population has a life expectancy of at least 85 years. The lower starting point in Sub-Saharan Africa means that this threshold is not reached by 2100 across all scenarios (see Supplementary Material 1.2). Consequently, in SSP1 the health index increases by 37% in sub-Saharan Africa, but only by 5% in North America. However, in addition to saturation, future rates of change in sub-Saharan Africa seem to imply a necessary socio-economic convergence with other global regions: even in the SSP3 “rocky road” scenario, health and education outcomes and energy consumption all increase. Therefore, the extent to which future projections are overly dependent on scenario starting conditions, and whether a broad plausible range of possible futures is explored in our data is further addressed in Section 3.3.2 and the Discussion.

3.3 Pixel-level

3.3.1 Spatial pattern

Pixel-level variation in socio-economic capitals reveals striking spatial patterns. Both proportional changes over 2020-2100 (Figure 6a) and divergence within SSPs in 2100 (Figure 6b) are highly spatially autocorrelated

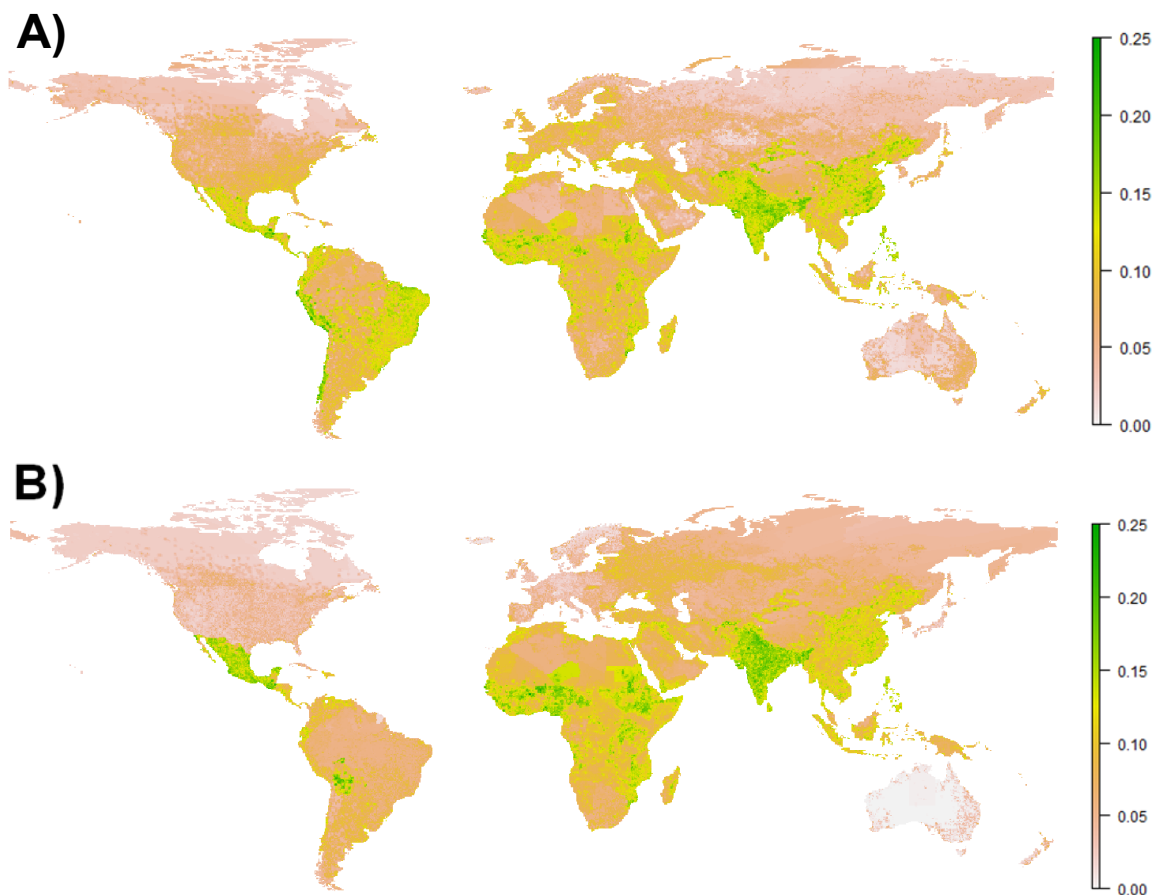


Figure 6: Pixel-level change in socio-economic capitals in the SSPs. A) mean proportional change from 2020 baseline values in 2100 under SSP2; B) mean proportional divergence across SSPs 1-5 in 2100. Both maps reveal hotspots of change in India, China and Sub-Saharan Africa, while there is greater change (A) than divergence (B) in South America, and the inverse relationship in Mexico.

(Moran's $I \geq 0.91$). Divergence over 2020-2100 in SSP2 (a "Middle of the Road" scenario) mirrors the regional results, with change most evident across Sub-Saharan Africa and South Asia. By contrast, divergence between SSPs in 2100 is spread more widely across continents, with hotspots in Peru, Germany, Northern India and Mexico. The causes of each divergent area are different, for example with market access due to rapid urbanisation in SSP5 driving the divergence in Germany whereas the Gini coefficient drives the divergent region in Peru.

3.3.2 Cluster analysis

Clustering of the SSP-variation index for 2100 reveals four clusters with distinct capital signatures (Figure 7). Clusters in 2100 describe not absolute state, but differences in values between SSPs. In 2100, Cluster 1 describes pixels with little divergence across SSPs. Cluster 2 pixels diverge substantially for market access and energy consumption, but less so for working age population, education and inequality (i.e. Gini) outcomes. Cluster 3 pixels have divergent outcomes for education and working age population, but interestingly less so for inequality and energy consumption. Cluster 4 diverges most for the Gini coefficient, energy consumption and working age population.

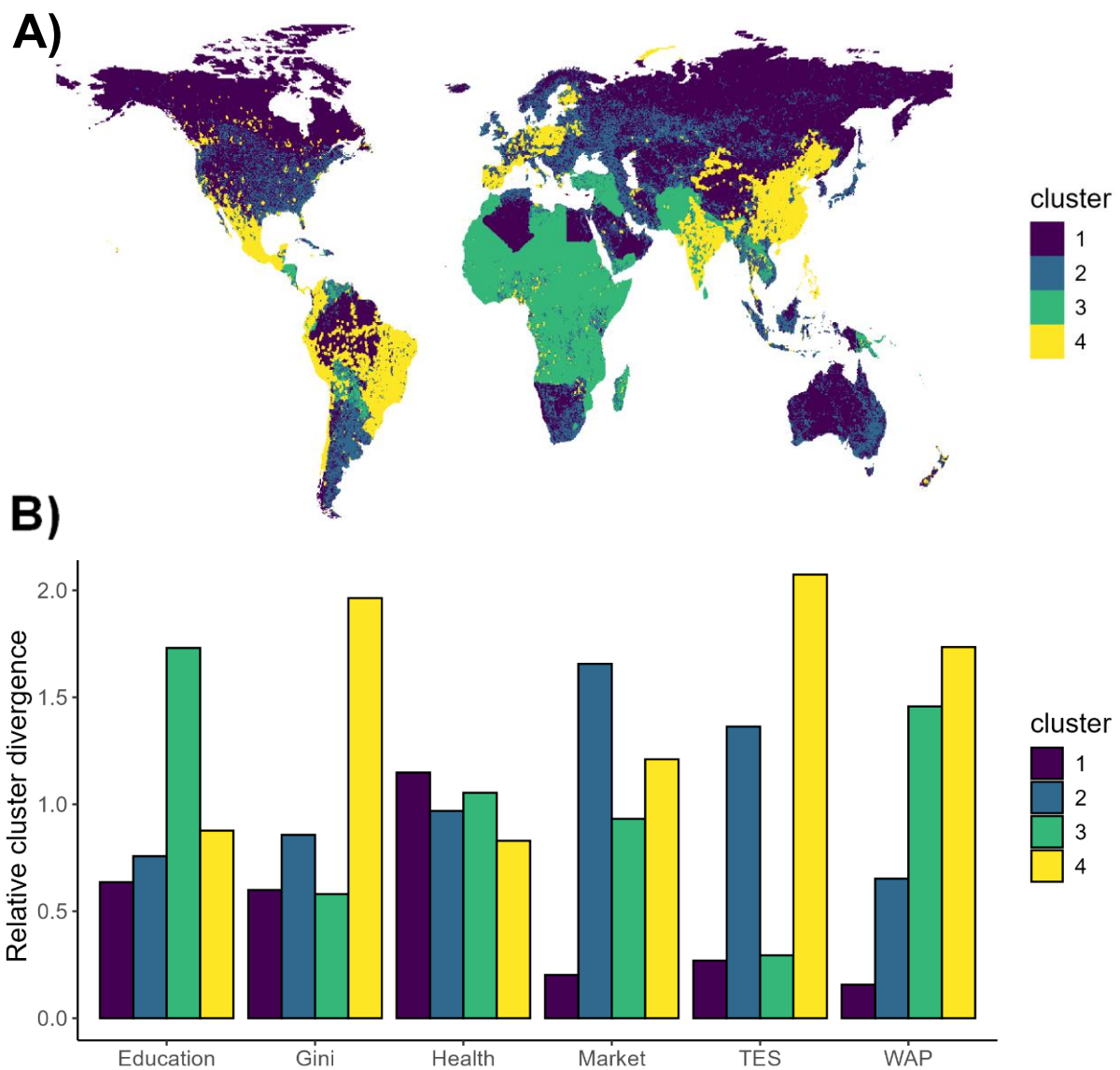


Figure 7: K-means clustering of divergence across SSPs among six socio-economic capitals in 2100. Clusters reveal cross-continental, yet spatially-coherent patterns of divergence, and so predicted trajectories through the SSPs at a pixel-level.

In addition, cluster trajectories through the SSPs are strongly correlated with their baseline values in 2020 ($r = 0.74$, $p < 0.0001$). Notably, Cluster 1, which is dominated by the boreal forests and several deserts (Figure 7) has low values for energy consumption, market access and working age population in 2020 and hence diverges little across the SSPs (Figure 8). What divergence there is in such regions is weighted towards indicators calculated at the sub-national region level (i.e. education and health). Conversely, Cluster 4, which is characterised by densely populated and urbanised areas, particularly in developing nations, begins with above average values for energy consumption, working age population and inequality (Gini) in 2020, and subsequently diverges strongly for these indicators across SSPs. Interestingly, market access diverges most not in Cluster 4 - which has highest values for this indicator in 2100 - but in Cluster 2, which is characterised by (peri-)urban areas in richer nations. Finally, Cluster 3, which covers many rural areas in developing countries, particularly in Sub-Saharan Africa, has lower-than-average values in 2020 for education and working age population, but diverges strongly for these capitals. For the case of education, this above average divergence may be linked to the saturation of this index in other world regions (discussed further below).

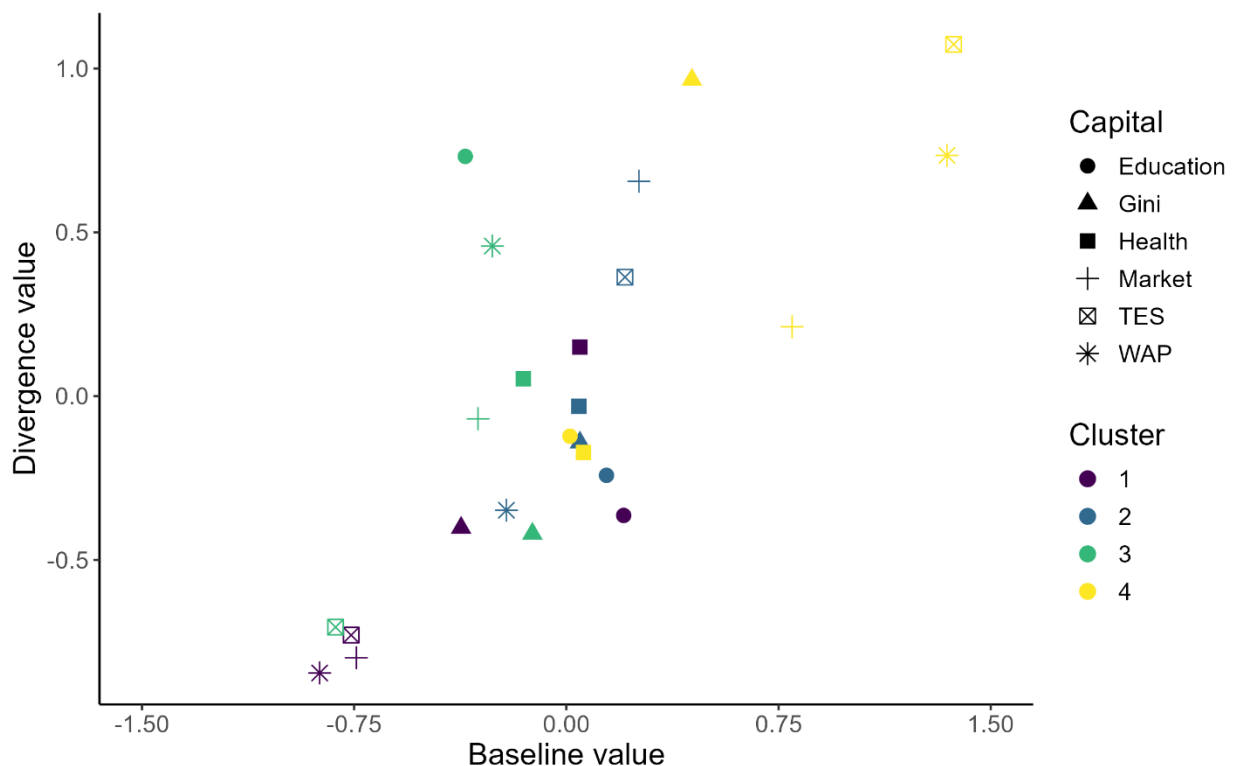


Figure 8: Patterns of variation in socio-economic capitals between SSPs for 2100. Clusters are identified through k-means clustering; 'Baseline value' is the arithmetic mean of normalized (mini-max) indicator values for 2020; 'Divergence value' is the mean of ranges of normalized (mini-max) indicator values across the SSPs in 2100; Key: Market = market access, WAP = working age population, TES = total energy supply.

4. Discussion

This study has presented a new set of gridded geospatial projections for the SSPs of six agent-capitals for use in socio-environmental modelling. These capitals enable far more detailed and complete exploration of SSP scenario space than has so far been possible, so that outcomes generated solely based on GDP and population change can be properly evaluated and new outcomes revealed. Discussion here focuses first on key patterns identified in the new projections, before assessing their limitations, and ultimately whether our results point towards limitations in the SSP storylines themselves.

4.1 Key findings

Overall, the projections of human capitals presented here add additional indications about the human dimension of the SSPs in ways that are coherent with the underlying storylines. For example, life expectancy and

education increase most in SSP1 and 5, with worse outcomes under SSPs 3 and 4, particularly in Sub-Saharan Africa.

The value added by these new capital projections to the SSP storylines is perhaps most evident in the clustering. Four distinct clusters of trajectories through the SSPs emerge that across continental boundaries (Figure 7). It is notable, for example, that areas of South America and southern Africa fall under cluster 2, which includes much of the USA and Australia, whilst much of eastern China falls into cluster 4 with much of India, South and Central America. These differences can be explained by their relative starting positions on the Gini index and working age population: cluster 4 initially has much more inequality and higher populations than cluster 2, and hence diverges more strongly among these indicators.

There are also important differences amongst more rural clusters (i.e. cluster 1 and cluster 3). In 2100, cluster 1 has the least absolute change across indicators under SSP2 (a middle of the road scenario; mean of 0.045), whilst cluster 3 has the highest mean absolute change (mean of 0.088). This highlights the importance of using spatial projections of indicators for modelling which can capture intra-country dynamics. This is particularly pertinent for land system modellers, who may be left with a misleading impression of how far land use patterns and their impacts may change based on national-scale numbers alone.

4.2 Data and scenario limitations

An important distinction emerging in our projections is between those where the maximum possible attainable value is bounded either ontologically (through normative or other economic feasibility judgement) *versus* where the maximum possible value has unclear implications for real-world processes. In particular, the health and education indices have normative assumptions built into their construction, such as that no additional human flourishing is gained by increasing life expectancy beyond 85 years (UNDP, 2024). Similarly, market access saturates where travel time to a city is zero, whilst the Gini index saturates where wealth is all owned by a single person. Furthermore, in the SSP storylines themselves a judgement is made that population increase beyond a given threshold has overall negative consequences for wellbeing (O'Neill et al., 2017). Hence SSP1, with low challenges to climate adaptation and mitigation, has the lowest population growth (KC & Lutz, 2017).

By contrast, the upper limit of energy consumption has more ambiguous links to real-world processes and human wellbeing, leading to >150% increase in consumption in North America under SSP5. Perhaps more fundamentally, GDP is in effect unbounded and can continue to increase without clearly articulated direct impacts on societal processes or wellbeing. Whilst a HDI value of 1 has very clear real-world implications, a world with GDP 4x (SSP1) or >7x (SSP5) current levels would surely be extremely different from today - but in ways that are highly unclear and not specified by these scenarios.

Keys et al. (2024) argue that future scenarios used in environmental modelling explore only a very narrow portion of possible futures. In particular, they criticise the Shared Socioeconomic Pathways for “a refusal to look” – an unwillingness to consider either more radical justice-oriented economic transitions or reasonable worst case scenarios including forms of societal breakdown. There is surely some evidence to support their argument in our results. As examples, GDP increases in all scenarios (although it’s not clear why this should be the case), and for SSP1 (the most sustainability-focused scenario) energy consumption *increases* in North America despite population decreasing (suggesting even greater global per capita inequality in consumption; Figure 5). Even in the most pessimistic scenario (SSP3), health and education outcomes increase across all global regions by 2100 (Figure 5). Furthermore, the close correlation between indicator trajectories through the SSPs and their starting values (Figure 8) indicates there is surely scope for exploration of a wider range of outcomes across global regions.

Yet, we argue there is a grey area between a *refusal* to look and the basic impossibility of conceiving how technologies, political systems and associated socio-cultural values may evolve in the future. Our models can readily add zeros to the end of GDP figures, but we cannot imagine or articulate the implications of this for human societies. Therefore, comparison of our socio-economic capitals with GDP projections exposes a tension between assumptions around economic growth and our unwillingness or inability to imagine what this might actually mean. To some degree, this mirrors the arguments of Raworth (2018), that the lack of a coherent vision for the purpose of the economy has meant growth for its own sake has replaced any wider view of the goals of economic policy (Raworth, 2018). Furthermore, this tension indicates that in more fully exploring the human

dimensions of the SSPs, we may expose a lack of coherence and ability to represent distinct and plausible futures.

In addition to scenario constraints, there are important underlying limitations to the data presented here that potential users should consider. The choice of a 0.25° spatial resolution for the data was a product of two factors. Firstly, this reflects the limitations of some of the input data to our projections. For example, our projection of market access is dependent on the LUH2 projections of urban fraction, which are presented at a spatial resolution of 0.25° (Hurtt et al., 2020). Furthermore, our education and health projections reflect downscaling of data at the sub-national administrative level (Kummu et al., 2018). Secondly, the use of a constant 0.25° grid reflects a primary intended use of data in continental to global-scale coupled socio-ecological modelling, and particularly for the combination of behavioural models with dynamic global vegetation models (Arnell et al., 2014). Dynamic global vegetation models typically adopt a decimal-degree coordinate reference system at coarse resolution; for example, the Inter-Sectoral Impact Model Intercomparison Project provides climate and socio-economic forcing data at 0.5° (Frieler et al., 2024).

Therefore, the resolution of projections presented here is finer than those under standard usage for global modelling of climate change impacts on biomes, agriculture and fisheries. We argue that our adopted resolution is sufficient for the study of broad-scale trends. However, use of an unprojected (i.e. longitude, latitude) grid leads to a spatial distortion in the Northern high latitudes (see Supplementary Material 1.3). This may be an important consideration for modelling studies considering interactions between pixels – for example behavioural imitation within spatially-bounded farmer influence networks (Brown et al., 2022). In addition, the resolution of our data may be insufficient for studies focused on spatially heterogeneous processes. Cluster analysis pointed to the degree of urbanisation as an important driver of divergence in pixel trajectories, with clusters 1 and 3 primarily capturing rural areas, and clusters 2 and 4 capturing more urban areas (Figure 6). Yet, the resolution of data may make modelling of fire or other hazards in such peri-urban areas challenging, particularly where the configuration of urban and vegetated land covers at sub-grid level is important (Price et al., 2025). Future versions of the data could also improve representation of process. For example, the validity of our assumption that distance to coastline is proportional to port access will inevitably bias projections, and so approaches that incorporate land transport networks to ports (e.g. Castro Victoria et al., 2021) would be useful, particularly at finer spatial resolutions. Overall, we encourage users to think critically about the limitations and underlying basis of our projections before deciding whether they are suitable for a given modelling study.

5. Conclusion

This paper has presented a new set of projections for the SSPs for six socio-economic capitals. Spanning human, financial, social and infrastructural capitals, these new indicators add detail to the SSP storylines and support geospatial modelling of socio-environmental systems. In particular, the indicators highlight the importance of taking a spatial approach to capture rural-urban divergence within countries. However, the apparently limited scenario space captured by the capitals also poses questions about how representative the SSPs are of a range of plausible futures. Furthermore, the more limited scale of change in our socio-economic capitals relative to GDP projections highlights a tension between projecting indicators that are ontologically or normatively bounded versus those that are theoretically unbounded, yet with unclear real-world implications of large future increases.

Acknowledgements

OP and JDAM are supported by the Leverhulme Trust (grant no. RC-2018-023). AS, BS, CB and MR are supported by the KIT Future Fields Programme and the Helmholtz Excellence Initiative. The authors declare no conflict of interest. This paper contributes to the Global Land Programme (<https://glp.earth>).

Supplementary Material

The Supplementary Material for this article can be found online at <https://sesmo.org/article/view/18850/18508>.

References

- Ackerman, F., DeCanio, S. J., Howarth, R. B., & Sheeran, K. (2009). Limitations of integrated assessment models of climate change. *Climatic Change*, 95(3), 297–315. <https://doi.org/10.1007/s10584-009-9570-x>
- Arneth, A., Brown, C., & Rounsevell, M. D. A. (2014). Global models of human decision-making for land-based mitigation and adaptation assessment. *Nature Climate Change*, 4(7), Article 7. <https://doi.org/10.1038/nclimate2250>
- Bauer, N., Calvin, K., Emmerling, J., Fricko, O., Fujimori, S., Hilaire, J., Eom, J., Krey, V., Kriegler, E., Mouratiadou, I., Sytze de Boer, H., van den Berg, M., Carrara, S., Daiglou, V., Drouet, L., Edmonds, J. E., Gernaat, D., Havlik, P., Johnson, N., ... van Vuuren, D. P. (2017). Shared Socio-Economic Pathways of the Energy Sector – Quantifying the Narratives. *Global Environmental Change*, 42, 316–330. <https://doi.org/10.1016/j.gloenvcha.2016.07.006>
- Billing, M., Forrest, M., Bowring, S., Oberhagemann, L., Neidermeier, A., Hetzer, J., von Bloh, W., Muller, C., Rolinski, S., Hickler T., & Thonicke, K. (2026). Future projections of burned area in Europe highlight the importance of human action. *Global Change Biology*, 32 (8) e71043. <https://doi.org/10.1111/gcb.71043>
- Blanco, V., Brown, C., Holzhauser, S., Vulturius, G., & Rounsevell, M. D. A. (2017). The importance of socio-ecological system dynamics in understanding adaptation to global change in the forestry sector. *Journal of Environmental Management*, 196, 36–47. <https://doi.org/10.1016/j.jenvman.2017.02.066>
- Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, 13(2), 167–188. <https://doi.org/10.1093/reep/rez004>
- Brown, C., Holman, I., & Rounsevell, M. (2021). How modelling paradigms affect simulated future land use change. *Earth System Dynamics*, 12(1), 211–231. <https://doi.org/10.5194/esd-12-211-2021>
- Brown, C., Seo, B., Alexander, P., Burton, V., Chacón-Montalván, E. A., Dunford, R., Merkle, M., Harrison, P. A., Prestele, R., Robinson, E. L., & Rounsevell, M. (2022). Agent-Based Modeling of Alternative Futures in the British Land Use System. *Earth's Future*, 10(11), e2022EF002905. <https://doi.org/10.1029/2022EF002905>
- CIESIN (Center for International Earth Science Information Network) - Columbia University. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC). <https://doi.org/10.7927/H49C6VHW>.
- de Castro Victoria, D., da Silva, R.F.B., Millington, J.D., Katerinchuk, V. & Batistella, M. (2021) Transport cost to port through Brazilian federal roads network: Dataset for years 2000, 2005, 2010 and 2017. *Data in brief*, 36, 107070. <https://doi.org/10.1016/j.dib.2021.107070>
- EIA (U.S. Energy Information Administration). Global energy consumption [online resource]. Available at: <https://www.eia.gov/opendata/bulkfiles.php>, last accessed 15 Nov 2024.
- EI (Energy Institute). (2024). Statistical review of world energy [online resource]. Available at: <https://www.energyinst.org/statistical-review>, last accessed 15 Nov 2024.
- Frieler, K., Volkholz, J., Lange, S., Schewe, J., Mengel, M., Lopez, M., Otto, C., Reyer, C., Karger, D., Malle, J., True, S., Menz, C., Blanchard, J., Harrison, C., Petrik, C., Eddy, T., Ortega-Cisneros, Novaglio, C., ... & Bechtold, M. (2024). Scenario setup and forcing data for impact model evaluation and impact attribution within the third round of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP3a). *Geoscientific Model Development*, 17, 1-51. <https://doi.org/10.5194/gmd-17-1-2024>
- Gaffin, S. R., Rosenzweig, C., Xing, X., & Yetman, G. (2004). Downscaling and geo-spatial gridding of socio-economic projections from the IPCC Special Report on Emissions Scenarios (SRES). *Global Environmental Change*, 14(2), 105–123. <https://doi.org/10.1016/j.gloenvcha.2004.02.004>
- Hausfather, Z., & Peters, G. (2020). Emissions - the 'business as usual' story is misleading. *Nature*, 577, 618-620. <https://doi.org/10.1038/d41586-020-00177-3>
- Hijmans, R. (2025). terra: spatial data analysis [software], version 1.10. Available at: <https://CRAN.R-project.org/package=terra>, last accessed 6 November 2025.
- Hurt, G. C., Chini, L., Sahajpal, R., Froking, S., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fisk, J., Fujimori, S., Klein Goldewijk, K., Hasegawa, T., Havlik, P., Heinemann, A., Humpenöder, F., Jungclauss, J., Kaplan, J. O., Kennedy, J., Krisztin, T., Lawrence, D., ... & Zhang, X. (2020). Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6. *Geoscientific Model Development*, 13(11), 5425–5464. <https://doi.org/10.5194/gmd-13-5425-2020>
- Jones, B., & O'Neill, B. C. (2016). Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways. *Environmental Research Letters*, 11(8), 084003. <https://doi.org/10.1088/1748-9326/11/8/084003>
- KC, S., & Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, 42, 181–192. <https://doi.org/10.1016/j.gloenvcha.2014.06.004>
- Keys, P. W., Badia, L., & Warrier, R. (2024). The Future in Anthropocene Science. *Earth's Future*, 12(1), e2023EF003820. <https://doi.org/10.1029/2023EF003820>
- Koch, J., & Leimbach, M. (2023). SSP economic growth projections: Major changes of key drivers in integrated assessment modelling. *Ecological Economics*, 206, 107751. <https://doi.org/10.1016/j.ecolecon.2023.107751>
- Kummu, M., Taka, M., & Guillaume, J. H. A. (2018). Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. *Scientific Data*, 5(1), Article 1. <https://doi.org/10.1038/sdata.2018.4>
- Mahmoud, M. R., Roushdi, M., & Aboelkhear, M. (2024). Potential benefits of climate change on navigation in the northern

- sea route by 2050. *Scientific Reports*, 14(1), 2771. <https://doi.org/10.1038/s41598-024-53308-5>
- Meijer, J. R., Huijbregts, M. A. J., Schotten, K. C. G. J., & Schipper, A. M. (2018). Global patterns of current and future road infrastructure. *Environmental Research Letters*, 13(6), 064006. <https://doi.org/10.1088/1748-9326/aabd42>
- Millington, J. D. A., Katerinchuk, V., Silva, R. F. B. da, Victoria, D. de C., & Batistella, M. (2021). Modelling drivers of Brazilian agricultural change in a telecoupled world. *Environmental Modelling & Software*, 139, 105024. <https://doi.org/10.1016/j.envsoft.2021.105024>
- Mirza, M. U., Xu, C., Bavel, B. V., Van Nes, E. H., & Scheffer, M. (2021). Global inequality remotely sensed. *Proceedings of the National Academy of Sciences*, 118(18), e1919913118. <https://doi.org/10.1073/pnas.1919913118>
- Murakami, D., Yoshida, T., & Yamagata, Y. (2021). Gridded GDP Projections Compatible With the Five SSPs (Shared Socioeconomic Pathways). *Frontiers in Built Environment*, 7. <https://www.frontiersin.org/articles/10.3389/fbuil.2021.760306>
- Murray-Rust, D., Brown, C., van Vliet, J., Alam, S. J., Robinson, D. T., Verburg, P. H., & Rounsevell, M. (2014). Combining agent functional types, capitals and services to model land use dynamics. *Environmental Modelling & Software*, 59, 187–201. <https://doi.org/10.1016/j.envsoft.2014.05.019>
- NASA (2009). Distance to the nearest coastline [online resource]. Available at: <https://oceanscolor.gsfc.nasa.gov/resources/docs/distfromcoast/>, last accessed November 4 2025.
- Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., ... Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, 520(7545), Article 7545. <https://doi.org/10.1038/nature14324>
- O'Neill, B. C., Carter, T. R., Ebi, K., Harrison, P. A., Kemp-Benedict, E., Kok, K., Kriegler, E., Preston, B. L., Riahi, K., Sillmann, J., van Ruijven, B. J., van Vuuren, D., Carlisle, D., Conde, C., Fuglestedt, J., Green, C., Hasegawa, T., Leininger, J., Monteith, S., & Pichs-Madruga, R. (2020). Achievements and needs for the climate change scenario framework. *Nature Climate Change*, 10(12), 1074–1084. <https://doi.org/10.1038/s41558-020-00952-0>
- O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, 42, 169–180. <https://doi.org/10.1016/j.gloenvcha.2015.01.004>
- O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., & van Vuuren, D. P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, 122(3), 387–400. <https://doi.org/10.1007/s10584-013-0905-2>
- Panwar, V., & Sen, S. (2019). Economic Impact of Natural Disasters: An Empirical Re-examination. *Margin: The Journal of Applied Economic Research*, 13(1), 109–139. <https://doi.org/10.1177/0973801018800087>
- Perkins, O., Kasoar, M., Voulgarakis, A., Edwards, T., Haas, O., & Millington, J. D. A. (2025a). The Spatial Distribution and Temporal Drivers of Changing Global Fire Regimes: A Coupled Socio-Ecological Modeling Approach. *Earth's Future*, 13(5), e2024EF004770. <https://doi.org/10.1029/2024EF004770>
- Perkins, O., Haas, O., Kasoar, M., Voulgarakis, A., & Millington, J. D. A. (2025b). Structural uncertainty in the direct human forcing of future global burned area. *EGU sphere*, <https://doi.org/10.5194/egusphere-2025-3728>
- Perkins, O., Kasoar, M., Voulgarakis, A., Smith, C., Mistry, J., & Millington, J. D. A. (2024). A global behavioural model of human fire use and management: WHAM! v1.0. *Geoscientific Model Development*, 17(9), 3993–4016. <https://doi.org/10.5194/gmd-17-3993-2024>
- Perkins, O., Matej, S., Erb, K., & Millington, J. (2022). Towards a global behavioural model of anthropogenic fire: The spatiotemporal distribution of land-fire systems. *Socio-Environmental Systems Modelling*, 4, 18130–18130. <https://doi.org/10.18174/sesmo.18130>
- Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., ... Vuuren, D. P. van. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, 42, 331–345. <https://doi.org/10.1016/j.gloenvcha.2016.10.002>
- Potancoková, M., K. C. S., & Goujon, A. (2014, April). Global Estimates of Mean Years of Schooling: A New Methodology [Monograph]. IR-14-005. <https://iiasa.dev.local/>
- Price, O., Ondei, S., & Bowman, D. (2025). Progress and prospects for predicting wildfire spread through the wildland-urban interface. *International Journal of Disaster Risk Reduction*, 121, 105392. <https://doi.org/10.1016/j.ijdr.2025.105392>
- Rabin, S. S., Melton, J. R., Lasslop, G., Bachelet, D., Forrest, M., Hantson, S., Kaplan, J. O., Li, F., Mangeon, S., Ward, D. S., Yue, C., Arora, V. K., Hickler, T., Kloster, S., Knorr, W., Nieradzik, L., Spessa, A., Folberth, G. A., Sheehan, T., ... Arneth, A. (2017). The Fire Modeling Intercomparison Project (FireMIP), phase 1: Experimental and analytical protocols with detailed model descriptions. *Geoscientific Model Development*, 10(3), 1175–1197. <https://doi.org/10.5194/gmd-10-1175-2017>
- Rao, N. D., Sauer, P., Gidden, M., & Riahi, K. (2019). Income inequality projections for the Shared Socioeconomic Pathways (SSPs). *Futures*, 105, 27–39. <https://doi.org/10.1016/j.futures.2018.07.001>
- Raworth, K. (2018). *Doughnut Economics: Seven Ways to Think Like a 21st Century Economist*. Chelsea Green Publishing.
- Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaserna, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., ... Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An

- overview. *Global Environmental Change*, 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>
- Ritchie, H., Rosado, P., and Roser, M. Primary energy consumption per capita [online resource], available at: <https://ourworldindata.org/grapher/per-capita-energy-use>, last accessed 15 Nov 2024.
- Rouhette, T., Van de Ven, D., Narayan, K., Tebaldi, C., Perkins, O., Haas, O., & Escobar, N. (2026). IAM-FIRE: A climate emulator-based framework to project wildfire impacts and risks for integrated assessment models. *Global Change Biology*, 32 (6), e70951. <https://doi.org/10.1111/gcb.70951>
- Saxena, A., Brown, C., Winkler, K., Arneth, A., & Rounsevell, M. (2026). Spatial patterns of global land management intensity are influenced by socioeconomic, biophysical and behavioural factors. *Earth System Science Data*, 18 (9), 6251–6292. <https://doi.org/10.5194/essd-18-6251-2026>
- Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., & Owen, A. (2016). Decoupling global environmental pressure and economic growth: Scenarios for energy use, materials use and carbon emissions. *Journal of Cleaner Production*, 132, 45–56. <https://doi.org/10.1016/j.jclepro.2015.06.100>
- Teckentrup, L., Harrison, S. P., Hantson, S., Heil, A., Melton, J. R., Forrest, M., Li, F., Yue, C., Arneth, A., Hickler, T., Sitch, S., & Lasslop, G. (2019). Response of simulated burned area to historical changes in environmental and anthropogenic factors: A comparison of seven fire models. *Biogeosciences*, 16(19), 3883–3910. <https://doi.org/10.5194/bg-16-3883-2019>
- Thorndike, R. L. (1953). Who belongs in the family? *Psychometrika*, 18(4), 267–276. <https://doi.org/10.1007/BF02289263>
- UNDESA (United Nations Department of Economic and Social Affairs). World Population Prospects [online resource]. Available at: <https://population.un.org/wpp/Download/Standard/Population/>, last accessed 15 Nov 2024.
- UNDP (United Nations Development Programme). (2025). Human Development Report 2025 technical notes. Available at: <https://hdr.undp.org/data-center/documentation-and-downloads>, last accessed 12 Oct 2026.
- Verburg, P. H., Ellis, E. C., & Letourneau, A. (2011). A global assessment of market accessibility and market influence for global environmental change studies. *Environmental Research Letters*, 6(3), 034019. <https://doi.org/10.1088/1748-9326/6/3/034019>
- World Bank. The world by region [online resource]. Available at: <https://datatopics.worldbank.org/sdgatlas/archive/2017/the-world-by-region.html>, last accessed 21 Nov 2024.
- Wright, M. N., & Ziegler, A. (2017). ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. *Journal of Statistical Software*, 77, 1–17. <https://doi.org/10.18637/jss.v077.i01>