



Downscaling population and urban land use for socio-economic scenarios in the UK

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Abstract

Projecting the distribution of population is critical in supporting analysis of the impacts and risks associated with climate change. In this paper, we apply a computational algorithm parameterised for the UK Shared Socioeconomic Pathway (UK-SSP) narratives to create 1-km gridded urban land use and population projections for the UK to the end of the twenty-first century. Using a unimodal neighbourhood function, we model heterogeneity in urban sprawl patterns. The urban land use maps are used as weights to create downscaled population projections. We undertake a model uncertainty analysis using 500 simulations with varying parameter settings per UK-SSP. Results illustrate how sprawl can emerge from scenario conditions even when population numbers decline, and irrespective of socio-economic wellbeing. To avoid negative environmental externalities associated with uncontrolled sprawl, such as in UK-SSP5 and UK-SSP3, planning policies will be vital. Uncertainties about future population development in the UK are higher in rural areas than in urban areas. This has an effect on the competition for land and influences confidence in projections of broader land system change.

Keywords Extended SSPs · UK projections · Spatial downscaling · Urban sprawl · Population scenarios · Land use change

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Introduction

Many analyses of climate impacts and risks require projections of urban land use and population at fine spatial resolutions. Finely gridded urban land use and population data can support risk assessments of drought, flooding, and sea level rise. They can also be used as input to mitigation research, investigations into biodiversity threats due to urban sprawl, as well as informing policy interventions including, for example, through spatial planning, water resource management, and infrastructure investments.

The Shared Socio-economic Pathways (SSP) is a framework of five scenarios adopted by the international climate research community in order to systematise uncertainty about future socioeconomic development (O'Neill et al. 2020, 2017, 2014). The SSPs describe changes in socio-economic conditions based on challenges to climate change adaptation and mitigation. They include scenarios focusing on global sustainability (SSP1), regional rivalry (SSP3), inequality (SSP4), fossil-fuelled development (SSP5) and a middle of the road scenario (SSP2). None of the SSPs is a business-as usual scenario, and the framework is set up to be independent from climate policy assumptions (Kriegler et al. 2014). At the aggregated global, regional and country level, SSP urbanisation projections have been created by Jiang and O'Neill (2017) and SSP population projections have been created by KC and Lutz (2017).

For local and subnational applications, various extended SSP narratives and quantitative projections have been created, which include local characteristics and provide data at finer sectoral and spatial resolutions (O'Neill et al. 2020). Quantitative SSP projections at 10' resolution for Europe have been created with the IMPRESSIONS dIAP model (<http://www.highendsolutions.eu/page/dIAP>), an integrated cross-sectoral model capturing socio-ecological interactions (Harrison et al. 2016). When analysing climate risks in a national context and particularly when considering population, however, a 10 arcmin. resolution (ca. 18.5 km at the equator, less towards the poles) can be too coarse.

To create finer resolution SSP projections, various downscaling methodologies have been developed and applied (van Vuuren et al. 2010). These include simple proportional scaling techniques (Boke-Olén et al. 2017; Yidan Chen et al. 2020a, b; Gaffin et al. 2004; Gao 2017, 2020), gravity-based approaches of intermediate complexity (Grübler et al. 2007; Jones & O'Neill 2016; Reimann et al. 2021) and other approaches ranging from qualitative stakeholder input-based methods (Rickebusch et al. 2011) to machine learning methods with resolutions as fine as 100-m grids (Yimin Chen et al. 2020a, b; Wolff et al. 2020). Each downscaling methodology comes with its own advantages and disadvantages (van Vuuren et al. 2010).

The simplest approach is proportional scaling, which has advantages in terms of efficiency and transparency but has the disadvantage of being inflexible. The approach has been criticised for leading to unrealistically high population numbers in densely populated areas, since population fractions in each cell are held constant (van Vuuren et al. 2010). An early application of this method for worldwide downscaled population projections was made by Gaffin et al. (2004) at 1/4° resolution. More recent studies include Gao (2017, 2020), who used proportional scaling to downscale Jones and O'Neill's (2016) worldwide population projections to 1-km resolution. Regional applications using the same approach for Africa (Boke-Olén et al. 2017) and for China (Yidan Chen et al. 2020a, b) have included more specificity by introducing a separate treatment of urban and rural areas.

Gravity-based approaches to downscaling allocate population in a more plausible way (van Vuuren et al. 2010). The calculation of population potentials as a function of distance to certain characteristics in order to downscale population scenarios for climate research goes back to Grübler et al. (2007) and has been employed in several more recent studies (Jones & O'Neill 2016 at 7.5' grid resolution for the world; Reimann et al., 2021 at 30' grid for the mediterranean region, considering the differences between coastal and inland areas). These studies have in common that they use parameterised functions to create population potentials or preferences, which then determine where population is allocated. Parameters for these functions are calibrated from historical data, usually based on observed changes between 1990 and 2000. A limitation of using gravity models to determine population allocation is that they naturally lead to agglomeration, as attractiveness increases with density (Grübler et al. 2007; Reimann et al. 2021).

In this study, we develop a new set of UK urban and population projections. Our approach offers advantages in terms of being consistent with the new quantitative UK-SSP scenarios (Merkle et al. 2022), being able to simulate leapfrogging urban sprawl, and considering UK-SSP-specific land exclusions. Leapfrogging means that new urban cells can emerge at some distance from existing urban cells. While earlier projections that include the UK have largely reproduced historically observed development (Gao 2017, 2020; Jones & O'Neill 2016), our projections provide a more accurate fit with the extended SSP narratives for the UK described in detail in Harmáčková et al. (2022) and Pedde et al. (2021).

The UK-SSP narratives (Harmáčková et al. 2022) and quantifications (Merkle et al., 2022) describe structurally different, plausible and coherent socio-economic scenarios for various sectors in the UK, for use in climate change impact research. In order to follow the UK-SSP narratives as closely as possible, we apply a gravity-based approach with a neighbourhood function that allows for leapfrogging

(Caruso et al. 2005). As a result, we avoid enforced urban agglomeration, which has been identified as a limitation in earlier gravity-based downscaling studies (Reimann et al. 2021). Given the unique and unobserved nature of the future UK-SSPs, we make no attempt to replicate historical patterns of change. However, we also undertake a Monte Carlo simulation to demonstrate the effect of input parameter uncertainty on the resulting patterns of urban land use and population.

Methodology

UK case study area

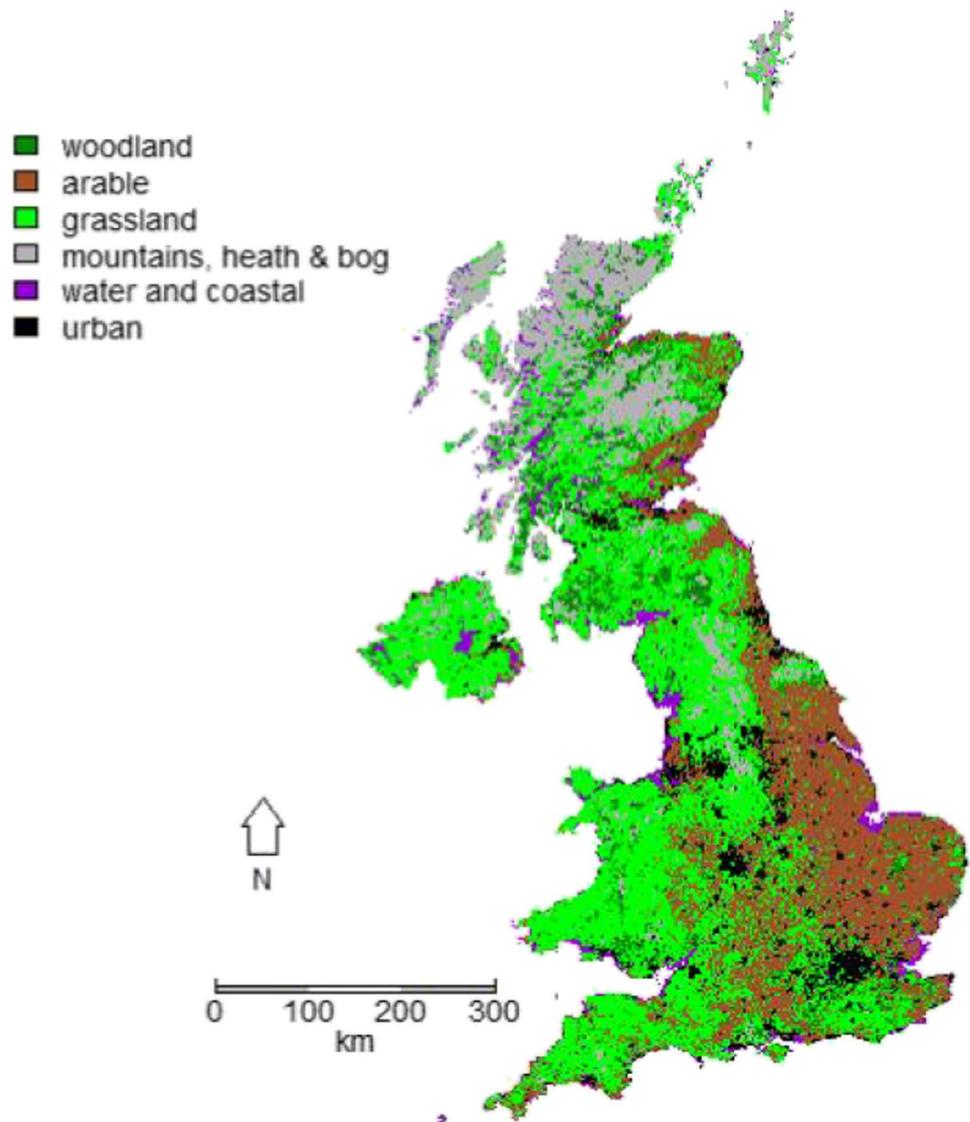
The UK is a country of 67 million people, covering Great Britain and Northern Ireland. It is the third largest European

country in terms of population (after Russia and Germany), and due to its comparably small geographical area, it ranks amongst the most densely populated countries in Europe (after the Netherlands and Belgium). The UK land surface amounts to 258,546 km², out of which 42% are grassland, 24% are arable land, 15% are mountains, heath and bog, 8% are woodland, 6% are urban and 5% are water and coastal (Rowland et al. 2017a, b) (Fig. 1).

Downscaling approach

The downscaling approach adopted in this study shares similarities with earlier gravity-based approaches but also incorporates novel elements. The approach was conducted in two steps. As is common with other land use models, the model allocates land according to suitability (Oakleaf et al. 2019) and combines top-down and bottom-up elements

Fig. 1 UK land use baseline



(Verburg & Overmars 2009). In the first step, 1-km gridded urban land use maps were downscaled from the UK-SSP parameterised dIAP model projections at 10' resolution (Harrison et al. 2016; Terama et al. 2019), using a unimodal neighbourhood function to calculate allocation suitability. In the second step, 1-km gridded population maps were downscaled from the local authority district (LAD) level UK-SSP projections (Merkle et al. 2022), using the downscaled urban land use as an input to the population allocation.

The method was implemented through a computational algorithm in R, parameterised to reflect UK-SSP-specific urban development derived from the UK-SSP narratives and semi-quantitative trends (Harmáčková et al. 2022). The algorithm was applied to LADs in decadal time steps from 2020 to 2100, thereby ensuring vertical consistency with the UK-SSP population projections (Merkle et al. 2022). The UK-SSP population projections are vertically consistent with the global SSP population projections (KC and Lutz 2017). Figure 2 provides an overview of the method.

Urban land use

Urban land use was downscaled from the regional urban growth (RUG) model (Terama et al. 2019), which is a sub-model of dIAP (Harrison et al. 2016), using a parameterised unimodal distribution function to allocate urbanisation suitability weights around existing urban cells (Fig. 2).

We parameterised the RUG sub-model of dIAP with sprawl control assumptions that ensured smooth trends and consistency with the UK-SSP narratives (Harmáčková et al. 2022). We assumed increasing levels of planning control in SSP1 and SSP4, and decreasing levels of planning control in SSP3 and SSP5. SSP2 was created as a weighted interpolation between SSP1 and SSP3. All parameter settings are reported in supplementary material 1.2. The dIAP output was reprojected from 10' grid cells to 1-km grid cells, and then to the LAD polygons by taking the mean across 1-km cells in each LAD.

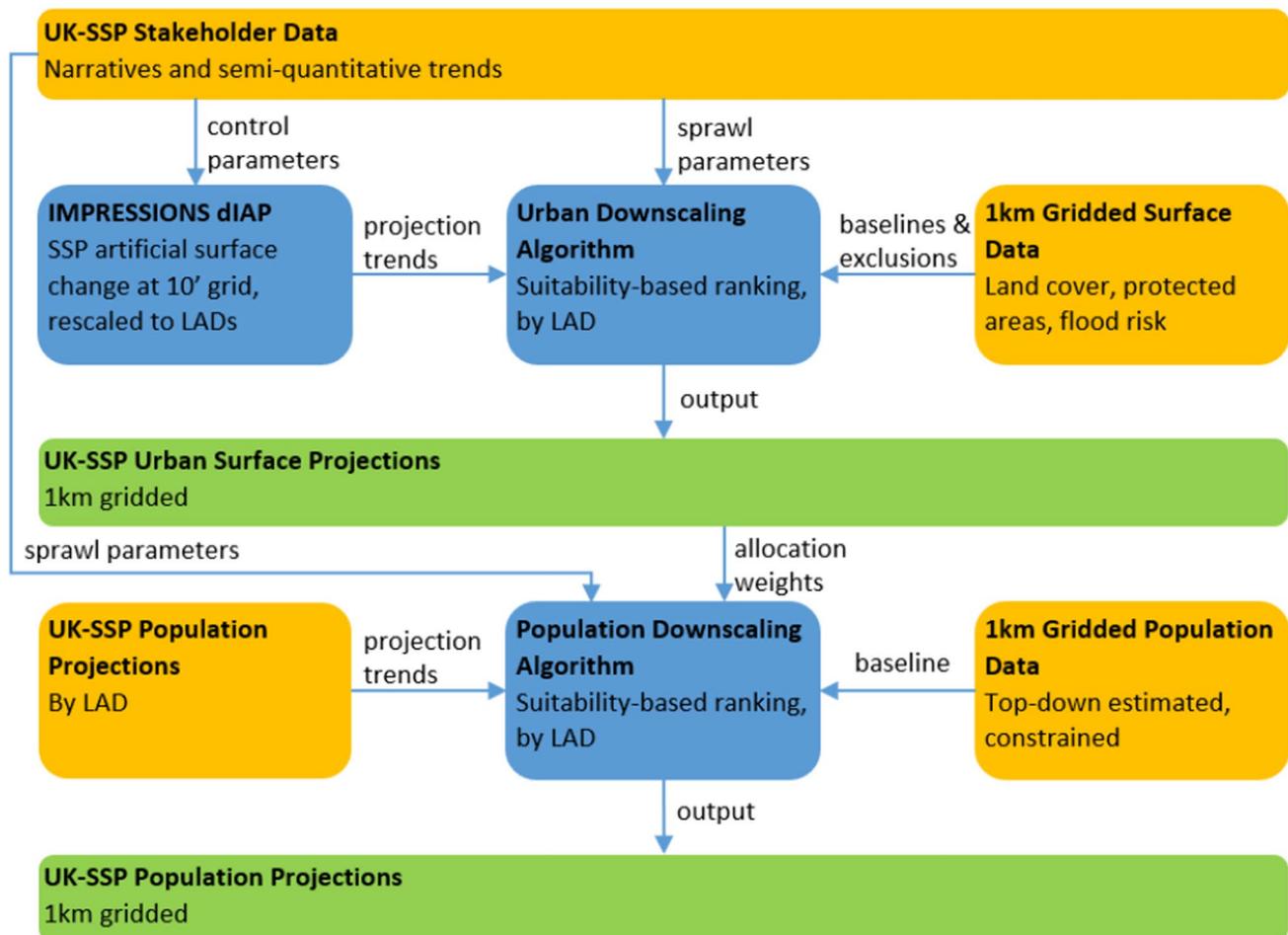


Fig. 2 Downscaling process encompassing an urban land use component and a population component. Yellow boxes for input data, blue boxes for models, green boxes for output data. LAD, *local authority districts*

As a baseline for the downscaled projections, we used the UKCEH Land Cover Map (LCM) 2015 at 1 km resolution (<https://www.ceh.ac.uk/services/land-cover-map-2015>) (Rowland et al. 2017a, 2017b). To exclude some areas from being urbanised, we applied UK-SSP specific masks for unsuitable land (e.g. marsh), protected areas (nature conservation) and flood risk zones. With these exclusions, the allocation of urban cells was more constrained in UK-SSP1 and UK-SSP2 than in the other scenarios, reflecting assumptions about the strictness of the implementation of land use planning. These assumptions are not explicit climate policy assumptions and so we relate them to the SSPs rather than the Shared climate Policy Assumptions of Kriegler et al. (2014). All exclusions are reported in supplementary material 1.3.

The number of new urban cells to be added per time step in every LAD and every scenario was a function of the number of urban cells in t_0 and the growth in urban area from t_0 to t_1 as projected by dIAP. New urban cells were assigned to the most probable location according to a suitability measure, which was based on proximity to existing urban cells in the previous timestep. We used a unimodal neighbourhood function with an exogenously selectable mode parameter to model the highest urbanisation suitability distance, and an exogenously selectable kurtosis parameter to model how quickly suitability decreases with distance from the mode. The underlying basis is a Kumaraswamy density function, transposed to make beta endogenous. With this framework, we could capture UK-SSP-specific sprawl assumptions about the extent of leapfrogging, which cannot be modelled with the negative exponential function that is usually used

in gravity-based downscaling (Reimann et al. 2021). Our framework provides the possibility for greenspace or agriculture to develop between new urban cells, and controls the scatter of urban development (Caruso et al. 2005). All steps to derive the urbanisation suitability function are described in supplementary material 1.4.

We predetermined the shape of the suitability function for each UK-SSP to make them reflect the UK-SSP narratives. We assumed that urbanisation likelihood is highest at moderate distance from current urban cells and then decreases with distance. The functions for each scenario are plotted in Fig. 3. The left end of the plot [0;0] is an urban cell, which has no suitability for urbanisation because it is already urban. Suitability then increases quickly with distance in all scenarios and reaches its maximum at between 2 and 3.5 km from existing urban cells, depending on the scenario.

In the rare case where there is no cell available, the algorithm assigns a new urban cell to an excluded cell with the highest rank. We accepted this behaviour as rogue urbanisation, assumed to occur because of imperfections in the planning process. The approach resulted in 1-km gridded maps of urban land use for each UK-SSP and each decade from 2020 until 2100.

Population

Population was downscaled from the LAD level UK-SSP population projections (Merkle et al. 2022), using the urban land use maps to weight the allocation of population change.

The baseline was created from a constrained top-down estimated dataset created by the WorldPop project (www.worldpop.org).

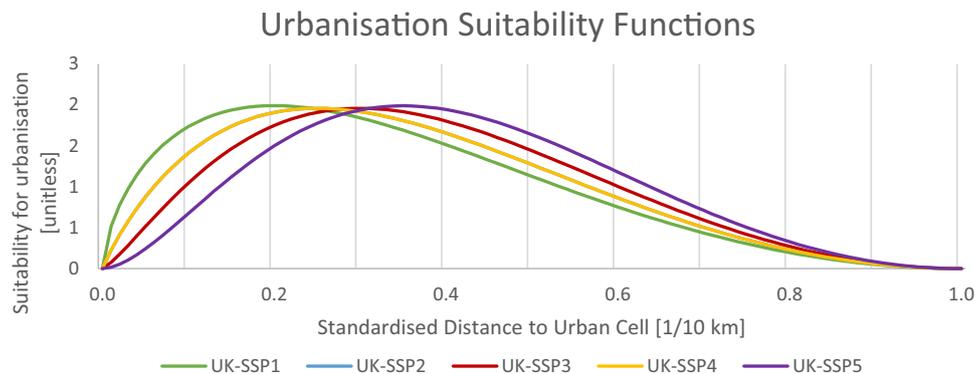


Fig. 3 Urbanisation suitability functions capturing UK-SSP-specific sprawl assumptions. Vertical lines denote cell boundaries when moving horizontally or vertically across the grid. The functions are derived from a Kumaraswamy distribution and provide urbanisation suitability for non-urban cells. We assume a neighbourhood boundary of 10 km — beyond this radius, no systematic urbanisation is likely. We assume the kurtosis parameter to be equal to 3, in order to have a smooth allocation of weights across the neighbourhood. UK-SSP 1: urban sprawl parameter set to 2 km. Dense development but allow-

ing for green space. A lower value would imply that non-urban cells between two urban cells would be highly unlikely. UK-SSP2: urban sprawl parameter set to 2.5 km. Development less dense than in UK-SSP1. UK-SSP3: urban sprawl parameter set to 3 km. Second-largest sprawl after UK-SSP5. UK-SSP4: urban sprawl parameter set to 2.5 km. Dense development but some sprawl due to the development of ghettos outside of city centres. UK-SSP5: urban sprawl parameter set to 3.5 km. Largest sprawl amongst all scenarios

worldpop.org) (Bondarenko et al., 2020). WorldPop data are based on official census data, downscaled statistically using satellite data on land surface, nightlight, road infrastructure and other ancillary inputs (Nieves et al., 2020). It is one of the most accurate population data sources available (Leyk et al., 2019). We aggregated these data to a 1-km grid resolution, clipped it to the UK LCM 2015 for consistency and scaled cells proportionally by LAD in order to align the data with the UK-SSP 2020 baseline.

As an input to the population downscaling process, we transformed the UK-SSP urban surface maps into urban weight maps (Fig. 4). Urban weight was defined as a function of distance to the nearest urban cell, adjacent urban cells and density of urban cells within circle neighbourhood windows of 5 km, 50 km and 150 km radius. The weighting function is described in supplementary material 2.2.

As with the urban land use downscaling approach, the population downscaling algorithm was applied to the LADs with a decadal time step for each scenario. The constrained nature of the baseline dataset implied that cells without population exist. In order to account for the possibility of unpopulated cells becoming populated, the algorithm evaluated eligibility according to exclusion criteria and urban weight changes. The amount of newly populated cells was assigned according to the existing populated extent and an exogenous

sprawl parameter. This rule ensured that population sprawl occurs in accordance with urbanisation, while taking the existing extent of population of the LAD into account. The assignment process for newly populated cells is described in supplementary material 2.3.

The algorithm then allocated LAD-level population change from Merkle et al. (2022) to each cell as a function of total population change and a cell's weight changes. This allocation mechanism is comparable to earlier gravity-based approaches (Grübler et al. 2007) and ensured that new gridded population took the projected urbanisation patterns into account, while remaining perfectly consistent with the LAD level projections. Population fractions depend on weight fractions and thus are able to change. The population allocation function is further described in supplementary material 2.4.

Key parameter assumptions

We translated the qualitative UK-SSP elements from Harmáčková et al. (2022) into parameter settings through an iterative process of expert reviews. All parameter settings are given in supplementary material 1.2, 1.3, and 3.1. We summarise these assumptions qualitatively in Table 1.

Fig. 4 Urban weight map examples as calculated in the framework

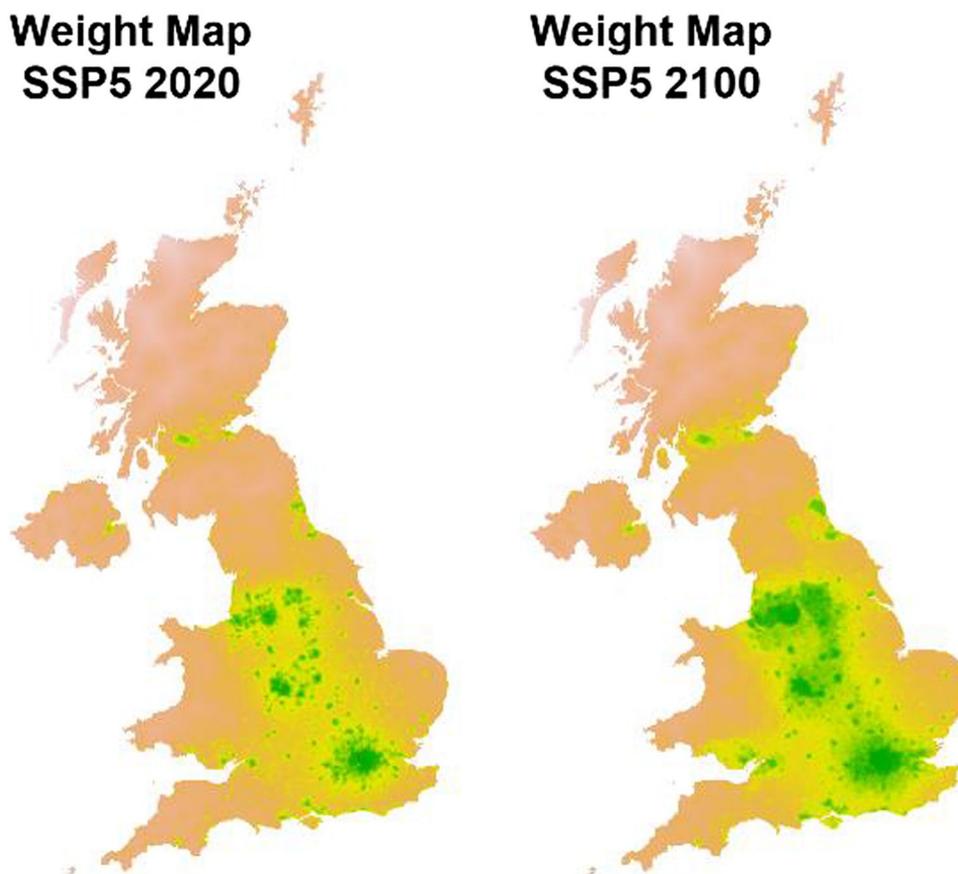


Table 1 Overview of assumptions for the UK-SSP scenarios, based on Harmáčková et al. (2022)

	UK-SSP 1	UK-SSP 2	UK-SSP 3	UK-SSP 4	UK-SSP 5
Key narrative components	Moderate population growth coupled with strict planning regulations and continued attractiveness of rural lifestyles leads to the growth of compact, green cities	Increasing urbanisation with strong centralised spatial planning leads to city-states by 2100	Breakdown in governance leads to uncontrolled urban sprawl and slums until 2070 then urban areas cease to grow as declining population	Strong governance of the elite coupled with high inequality results in moderate urban growth but with an increase in ghettos to 2070 after which the UK population ceases to grow	Strong sprawled urban development, resulting from weak spatial planning policy and high population increase
Exclusions for new urbanisation and new population (baseline maps)	Protected areas and flood risk areas are excluded from new development	Protected areas are excluded from new development	No exclusions other than unsuitable land surface	No exclusions other than unsuitable land surface	No exclusions other than unsuitable land surface
Planning control for dense areas (dIAP parameter)	Strongly increasing planning control in dense areas	N/A (not explicitly modelled by dIAP)	Decreasing planning control in dense areas	Strongly increasing planning control in dense areas	No change in planning control in dense areas
Planning control for areas of intermediate density (dIAP parameter)	Strongly increasing planning control in suburban and rural areas	N/A (not explicitly modelled by dIAP)	Strongly decreasing planning control in suburban and rural areas	No change in planning control in suburban and rural areas	Slightly decreasing planning control in suburban and rural areas
Urban sprawl (urbanisation downscaling algorithm parameter)	Very low setting, but allowing for green space between artificial surface cells	Low setting, urban development slightly less dense than in UK-SSP 1	Medium–High setting, second largest urban sprawl after UK-SSP 5	Low setting, dense development but some sprawl due to development of ghettos outside of city centres	High setting, largest urban sprawl of all scenarios
New populated land (population downscaling algorithm parameter)	Medium setting, less urban population than in UK-SSP 2, therefore slightly more population sprawl	Low setting, given that scenario assumes high urban population share	Medium–High setting, due to substantial population sprawl and no land use regulation	Low setting, given that scenario assumes high urban population share	High setting, higher than UK-SSP 3, due to massive sprawl and low land use restrictions

Analysis of uncertainty due to input parameters

We analysed the variability of the projections for urban area and population per UK-SSP when parameter settings are changed. We applied a Monte Carlo approach similar to Brown et al. (2014), running 500 simulations ($n = 500$) for each scenario, with combinations of randomly drawn settings. Parameter ranges were defined around the scenario-specific reference values, sampled from uniform distributions and varied simultaneously, rather than varying only one parameter at a time (Saltelli et al. 2019). We computed distributions of population sprawl, share of population on urban land, average population density and unevenness of population density, captured by the Gini coefficient (Duncan 1957). Finally, we computed the coefficient of variation for each cell to elicit where population allocation is most uncertain. Details about parameters and ranges for the analysis are provided in the supplementary section.

Results

Scenario runs

The UK-SSP narratives suggest significant urban and population sprawl patterns in UK-SSP3 and UK-SSP5 (scenarios with high challenges to climate change mitigation), and more dense development in UK-SSP1, UK-SSP2 and UK-SSP4 (scenarios with low to medium challenges to climate change mitigation) (Harmáčková et al. 2022). The model results presented here are consistent with this general picture and are summarised in Table 2 and in Figs. 5 and 6.

In UK-SSP1, the sustainability scenario, there is strong land use regulation leading to the exclusion of a large part of the UK from urban development in protected areas and flood risk zones. Even though total population increases by 27%, the model projects only a 22% increase in urban land cover between 2020 and 2100 due to planning controls.

Consequently, we observe an increase in average population density by 7%, as well as some sprawl into previously unpopulated land, due to rural livelihoods becoming more attractive (Harmáčková et al. 2022). The model suggests that populated land increases by 18%.

UK-SSP2, the middle of the road scenario, shares similarities with UK-SSP1, as population grows by 27%, and is allocated in a comparably dense way. Flood risk areas are not excluded, and urban sprawl is slightly larger than in UK-SSP1, while protected land is still excluded from urban development. Population sprawl is lower than in UK-SSP1, as development is focused on cities. As a result of the low number of eligible unpopulated cells to become newly populated, population density increases by 15%, which is more than in UK-SSP1, and reflects the narrative's focus on increased housing density in already populated areas

and movement of people from rural to urban environments (Harmáčková et al. 2022). Populated land increases by 10% — the smallest increase amongst all scenarios.

In UK-SSP3, the regional rivalry scenario, population declines by 26% as living conditions dramatically decrease, but urban land cover still increases. This development results from a lack of planning control and subsistence lifestyles requiring more space (Harmáčková et al. 2022). As many people become self-supporting, the model projects large population sprawl into unpopulated areas, as populated area increases by 49%. As illustrated in Figs. 5 and 6, only a few areas, mostly in rural Wales and Scotland, remain without population. Average population density decreases by 51%, which arises from the combined effect of population decline and sprawl.

UK-SSP4, the inequality scenario, has the lowest urban land cover growth and lowest population sprawl, largely

Table 2 Urban and population downscaling results

Indicator	Baseline 2020	UK-SSP 1 2100	UK-SSP 2 2100	UK-SSP 3 2100	UK-SSP 4 2100	UK-SSP 5 2100
Excluded land (exogenous parameter)	9.16%	36.48%	32.19%	9.16%	9.16%	9.14%
Urban land cover (exogenous, from dIAP)	5.92%	7.23%	7.27%	7.53%	7.08%	14.17%
Remaining potential land for urbanisation (endogenous)	84.92%	56.28%	60.55%	83.31%	83.77%	76.69%
Total population (exogenous, from global SSPs)	66.8 m	84.7 m	84.7 m	49.2 m	63.3 m	128.3 m
Populated land (endogenous)	50.0%	59.2%	55.2%	74.6%	57.7%	83.5%
Population on urban land (endogenous)	74.3%	73.9%	74.6%	72.6%	73.5%	78.1%
Population density across populated cells [people/km ²] (endogenous)	519	556	596	256	427	597

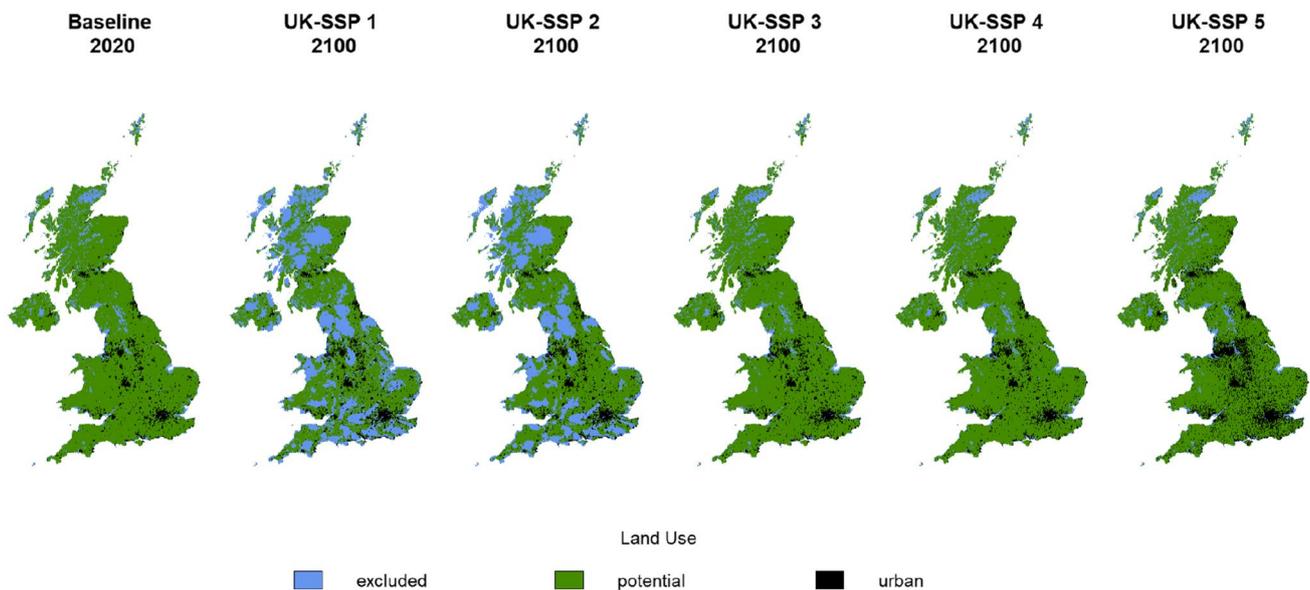


Fig. 5 Urban land use baseline and scenarios — UK

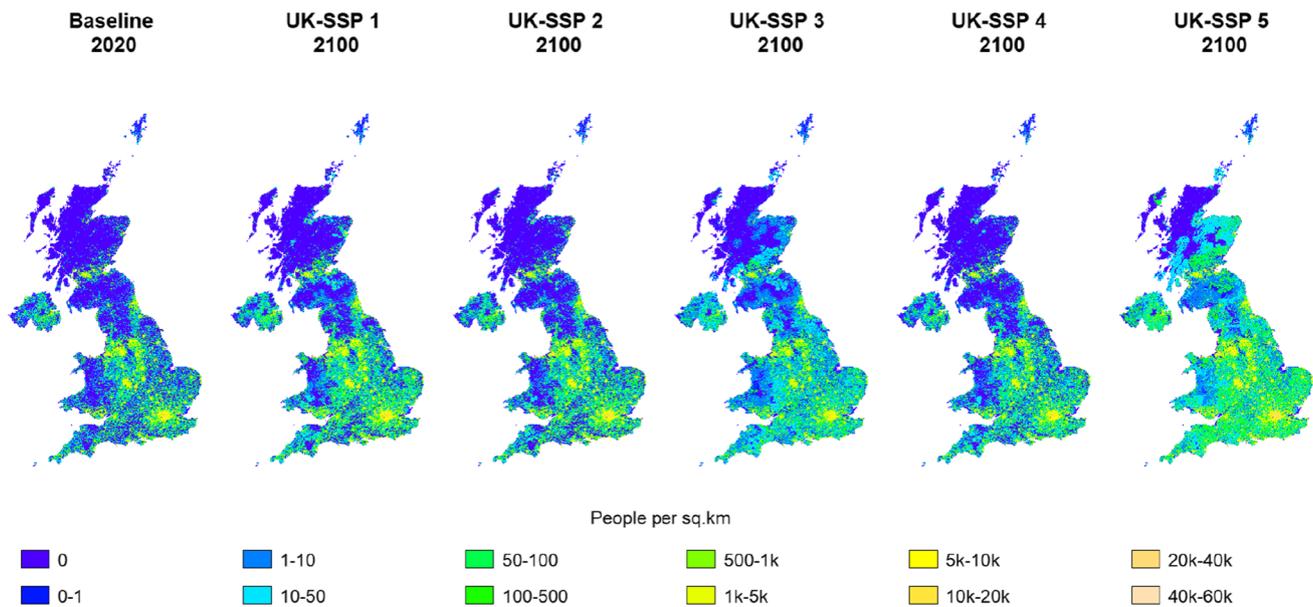


Fig. 6 Population baseline and scenarios — UK

due to a declining population and an economic focus on cities. As visible in Fig. 6, ghetto development around cities (Harmáčková et al. 2022) could be inferred, e.g. around Aviemore and Fort William in the Scottish Highlands.

UK-SSP5, the fossil-fuelled development scenario, is a scenario of massive urban sprawl and population growth, due to a near doubling of total population numbers and materially intensive growth of the economy (Harmáčková et al. 2022). The model projects a 139% increase in urban areas. Due to the large population sprawl, average population density reaches a similar level to UK-SSP2. As visible in Figs. 5 and 6, the development of “city-states” (Harmáčková et al. 2022) can be inferred around, e.g. Liverpool, Manchester, Sheffield and Birmingham, but also in other areas such as around Bristol/Cardiff and Glasgow/Edinburgh. With some exceptions in the Scottish Highlands and Islands, almost no part of the UK remains unpopulated.

Analysis of uncertainties due to model parameters

The Monte Carlo simulations with changes in input parameters per UK-SSP show that the number of populated cells, population on urban cells, population density and the heterogeneity of individual densities vary, which signifies uncertainty within the scenarios. Violin plots in Fig. 7 illustrate that the distributions of the output indicators are largely skewed, meaning that the effects from parameter changes are not linear. Correlation plots of parameter changes against indicator changes are provided in supplementary material 3.1.

Uncertainty ranges regarding the extent of populated land (top left plot, Fig. 7) and population densities (bottom

left plot, Fig. 7) are largest in UK-SSP 3 and UK-SSP 5 — an outcome from the high setting of the population sprawl parameter and large uncertainty range assumed for the parameter sample. While uncertainty on the extent of populated land (top left plot, Fig. 7) is negatively skewed in the majority of scenarios, uncertainty about urban population (top right plot, Fig. 7) is positively skewed in all scenarios and high outliers exist. Lowest uncertainty for the population share on urban cells is found in UK-SSP 5 — the scenario with the largest urban land cover extent. Uncertainty ranges on average population densities (bottom left plot, Fig. 7) are positively skewed and largest in UK-SSP 5. Heterogeneity of population density across cells (bottom right plot, Fig. 7) is generally high with a Gini coefficient ranging between 0.8 and 0.9. Heterogeneity is highest in UK-SSP3 and UK-SSP5, the scenarios assuming the highest level of urban and population sprawl.

The scenarios remain quite different from one another, despite the overlapping parameter ranges in the uncertainty analysis. Negative skewness of populated cells (top left plot, Fig. 7) is associated with reaching ceilings of areas that can become newly populated: given upper ceilings of available land that can realistically become populated, the relation between population and populated cells is not linear, but asymptotic. Therefore, more runs achieve higher rates than lower rates. Density has a reciprocal relationship to the extent of populated land, which is why we observe positive skewness of average density (bottom left plot, Fig. 7). Average density does not increase linearly with higher population numbers, because there is a tendency to populate new cells, which are constrained by availability. The population share

on urban cells is much less uncertain than the extent of populated land. This is particularly the case in UK-SSP5, where several LADs become fully urbanised. The distributions of the population share on urban cells in UK-SSP1–4 are multimodal. As revealed by the correlations shown in supplementary material 3.2, this outcome is related to low settings of the sprawl parameter, determining the level of urban land agglomeration in highly populated areas, and therefore altering the population share on urban land significantly.

For a spatial visualisation of uncertainties, we have calculated the coefficient of variation on population density (Fig. 8).

The coefficient of variation on population density for each cell across the Monte Carlo simulation results shows that uncertainty is generally low (<1%) in urban centres such as London, and in areas with very little possibility of changes. It is zero in areas that do not become populated in any simulation, either due to extreme remoteness (e.g. Uist in Scotland) or excluded land (e.g. northern Highlands in Scotland). Uncertainty is high in rural areas with higher allocation possibilities. Highest uncertainties prevail in UK-SSP3 and UK-SSP5, where population sprawl allows for more possibilities than in the more land use planning controlled scenarios. There are clear uncertainty hotspots, some of which occur across all scenarios. These include Ceredigion in Wales, Fermanagh and Omagh in Northern Ireland,

Inverness and Moray in Scotland and the Scottish Borders. The uncertainty hotspots have in common that they start off with low population numbers. Some of them are furthermore bound by large surrounding areas of unsuitable land.

Discussion

Using the downscaling process reported in this paper, we have created 1-km gridded UK-SSP projections of urban land use and population distributions. The downscaled projections cover the intermediate level between supranational projections (e.g. Gao 2017, 2020; Harrison et al. 2016; Jones & O'Neill, 2016; Reginster & Rounsevell 2006) and local projections at fine resolution (e.g. Fontaine & Rounsevell, 2009). The spatial patterns reflect the UK-SSP narratives reported in Harmáčková et al. (2022).

Uncertainties

The SSPs were developed to systematise uncertainty about future socio-economic development trends. While there is uncertainty about which SSP trajectory the future is likely to follow, if any, there is also uncertainty within each SSP and the tools used to explore them. Model outputs rely on

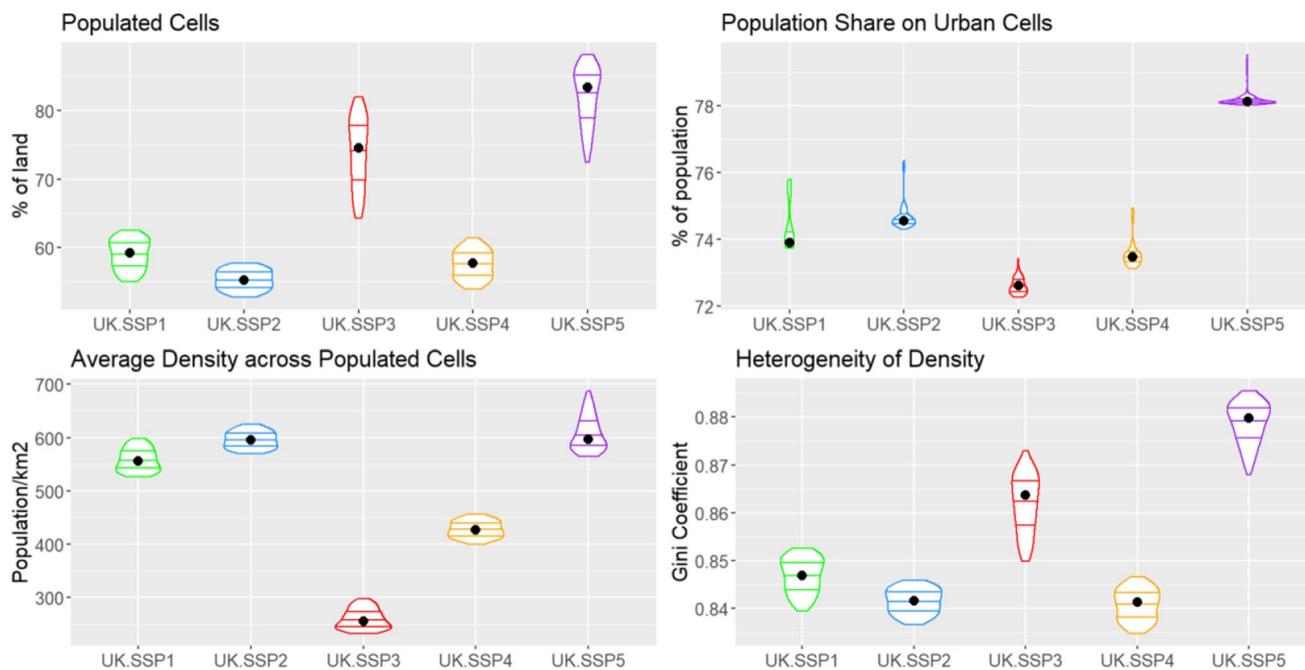


Fig. 7 Uncertainty distributions on selected indicators, plotted as violin plots. UK-SSP1 in green, UK-SSP2 in blue, UK-SSP3 in red, UK-SSP4 in yellow and UK-SSP5 in violet. The vertical extent of the plots shows the uncertainty ranges (bandwidths). The violin plots graphically show the distributions of results. Fat bottom ends means

positive skewness, and fat upper ends mean negative skewness. The horizontal lines inside the violin plots provide the 25th, 50th and 75th percentiles of the distribution. The black points in each plot indicate the result of the scenario reference run

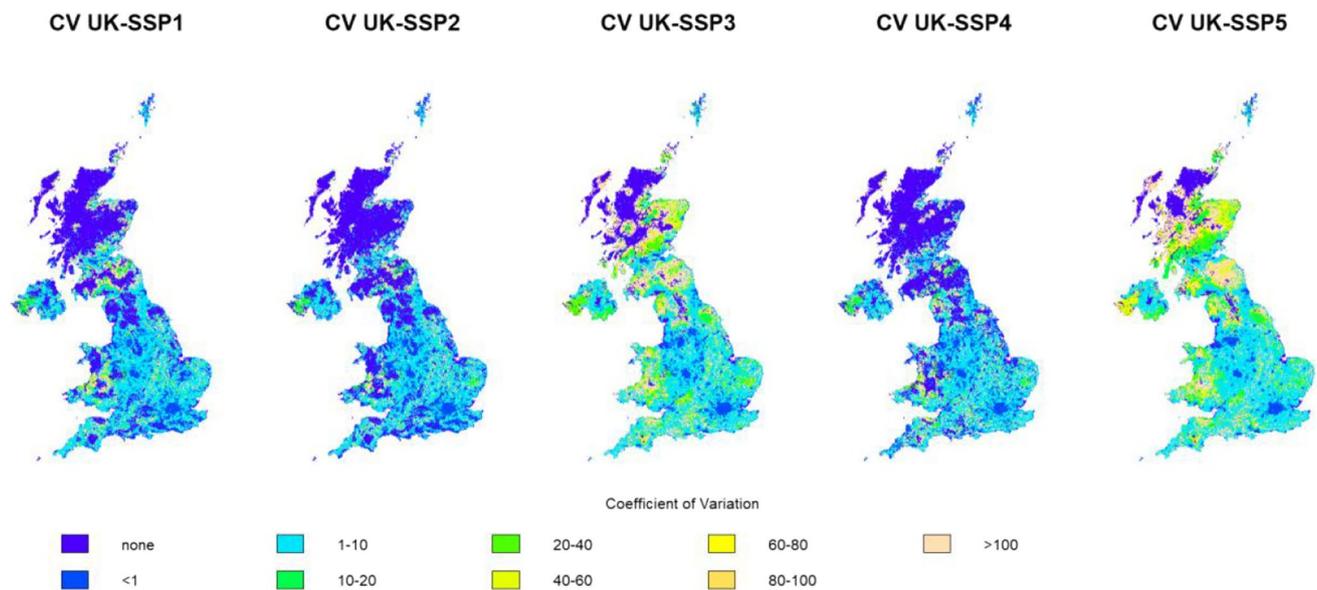


Fig. 8 Coefficient of variation plots

model structure, parameters and other inputs, all of which are not ontologically true (Rounsevell et al. 2021). Instead, they are subject to normative decisions about what reality the model should simulate.

To reduce uncertainty about parameter settings, many urbanisation and population scenario studies such as Merkmens et al. (2016) calibrate parameter settings from historic observations. This makes parameterisation reproducible, but it has the limitation that the model reproduces spatial patterns for future scenarios that replicate the patterns from an observed period in the past, e.g. 1990–2000 (Merkmens et al. 2016). Hence, there is no scope to produce novel urban patterns that differ from what occurred in the past. The parameter settings used here were not calibrated with historical data, since this allows future projections to deviate from historical patterns, in line with the UK-SSP storylines. We defined parameter settings based on scenario narratives, which are also uncertain, but have been co-created with stakeholder input (Harmáčková et al. 2022). We analysed uncertainties associated with the interpretation of these narratives (Rounsevell et al. 2021), showing how results vary when parameters settings per UK-SSP are changed. Similar to Reimann et al. (2021), we find that population allocation in urban areas is more certain than in rural areas. This reflects that rural LADs are larger than urban LADs, and therefore, the number of different possible urban land use and population allocations is larger in rural areas. However, the uncertainty in the urban model parameters did not substantially erode the differences between the scenario outcomes in terms of population distributions. This suggests that the general urbanisation characteristics are robust reflections of the broader scenario storylines.

Novelty

While some earlier population downscaling studies have employed proportional scaling techniques (Boke-Olén et al. 2017; Yidan Chen et al. 2020a, b; Gao 2017, 2020), we adopted a gravity-based approach (Grübler et al. 2007) with a specific parameterised urban allocation function that allowed for increased urban sprawl specified by the scenario narratives. The approach allows, therefore, for more spatial heterogeneity between scenarios. While some earlier downscaling approaches assumed fixed urban extents (Merkmens et al. 2016), we add to the growing body of downscaling studies that consider changing urban extents (Jones & O’Neill 2016; Reimann et al. 2021). Using an urban suitability function derived from the Kumaraswamy distribution, the downscaling model circumvents the agglomeration limitation of earlier gravity-based approaches (Reimann et al., 2021), so we can model more disaggregated urbanisation leapfrogging patterns. A further improvement of the approach presented here compared to some earlier gravity-based downscaling studies is that the UK-SSP-specific masks for urban and population sprawl take flood risk into account. The downscaled population projections are UK context-specific and more up to date than, e.g. Gao (2017, 2020), as they are based on recent historical baseline data from 2020 and on new LAD-level population projections (Merkle et al. 2022).

Consistency

We used a definition of urban land based on land cover rather than population density, and so the

urbanisation projections presented here are not consistent with the global SSP urbanisation scenarios (Jiang & O'Neill 2017), which work with a population density definition. In this case, the land cover-based definition of urban area was predicated on the availability of the existing dIAP-RUG urbanisation model (Harrison et al. 2016; Terama et al. 2019). The population projections, however, are consistent with the LAD level UK-SSP population scenarios (Merkle et al. 2022), which have been created to be consistent with the global population scenarios (KC and Lutz 2017). Population projections are therefore consistent across SSP scales.

Policy implications

Quantitative UK-SSP scenarios can be used in various ways to explore socio-economic uncertainties about the future and analyse the impacts of climate change (Harmáčková et al. 2022; Merkle et al. 2022). They are not forecasts, and likelihoods are not associated to the scenarios. A general limitation of the SSP framework is that climate change impacts are not considered, which is an important limitation for population scenarios (Jones & O'Neill 2016). If certain areas of the UK were, for example, to become increasingly prone to drought or flooding, then the population might be expected to migrate away from these areas. This cannot be considered without making assumptions about the impacts of climate change. Nevertheless, our projections can be used to inform policy about potential future environmental pressures and risks.

A comparison of the UK-SSP3 and UK-SSP5 results illustrates how large urban and population sprawl can develop, in the case of both population growth (UK-SSP5) and population decline (UK-SSP3). In UK-SSP5, sprawl is associated with a highly materialistic and expansive lifestyle, which assumes that socio-economic welfare is not dependent on the state of the natural environment (Harmáčková et al. 2022; Merkle et al. 2022). This scenario implies massive growth in transport infrastructure, to support a UK population that is nearly twice as large as today and has a resource-intensive economic metabolism. In UK-SSP3, sprawl is associated with poverty and the rise of an informal economy, which is resource-intensive due to inefficiencies associated with subsistence living. Both UK-SSP5 and UK-SSP3 are scenarios of weak land use planning policy, where people are free to settle anywhere, and there is no environmental protection to limit urban growth. UK-SSP1, UK-SSP2 and UK-SSP4 show that urban development can also be more constrained if stronger planning policy is in place, and similarly, this can occur for both a growing population (UK-SSP1, UK-SSP2) and a declining population (UK-SSP4).

Outlook

More precision in the model presented here could be achieved by adding more suitability variables, capturing for example elevation, slope and coastal proximity. While some preferences, e.g. coastal proximity, are considered in the dIAP RUG model underlying the urban projections (Terama et al. 2019), they are not explicitly considered in the downscaling process. More precision, requiring more input data, could be achieved by using spatially disaggregated data on economics, cultural and social features of interest, and including preferences for these features in the allocation algorithm (Li et al. 2016). Nevertheless, this should be done without compromising the transparency of model behaviour. The separation of model steps relating to urban change and population change, with each of their associated processes, can support this development.

Conclusion

The gridded urban land use and population projections presented in this study follow the UK-SSP narratives for spatially explicit challenges to climate change mitigation and adaptation in the UK. The downscaling approach takes leapfrogging explicitly into account and is therefore able to avoid unconstrained agglomeration patterns in scenarios where they do not fit the storylines developed with stakeholders. Urban and population sprawl can be modelled in scenarios of population growth as well as in scenarios of population decline. Strong land use planning leads to only moderate urbanisation in UK-SSP 1, even though population grows. Very dense development also occurs in UK-SSP 2 and in UK-SSP 4 as a result of the narratives' focus on city living. Even though population declines in UK-SSP 3, there is substantial sprawl into previously unpopulated land due to poverty and lack of planning. UK-SSP 5 is a scenario of massive sprawl into city states, where nearly no land remains available for nature. Projection uncertainties are shown to be higher in rural areas than in urban areas. These results highlight the vital importance of land use planning policies to avoid unsustainable futures.

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Declarations

Conflict of interest The authors declare no competing interests.

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