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Divergent urban land trajectories under alternative population projections within the Shared Socioeconomic Pathways

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Abstract

Population change is a main driver behind global environmental change, including urban land expansion. In future scenario modeling, assumptions regarding how populations will change locally, despite identical global constraints of Shared Socioeconomic Pathways (SSPs), can have dramatic effects on subsequent regional urbanization. Using a spatial modeling experiment at high resolution (1 km), this study compared how two alternative US population projections, varying in the spatially explicit nature of demographic patterns and migration, affect urban land dynamics simulated by the Spatially Explicit, Long-term, Empirical City development (SELECT) model for SSP2, SSP3, and SSP5. The population projections included: (1) newer downscaled state-specific population (SP) projections inclusive of updated international and domestic migration estimates, and (2) prevailing downscaled national-level projections (NP) agnostic to localized demographic processes. Our work shows that alternative population inputs, even those under the same SSP, can lead to dramatic and complex differences in urban land outcomes. Under the SP projection, urbanization displays more of an extensification pattern compared to the NP projection. This suggests that recent demographic information supports more extreme urban extensification and land pressures on existing rural areas in the US than previously anticipated. Urban land outcomes to population inputs were spatially variable where areas in close spatial proximity showed divergent patterns, reflective of the spatially complex urbanization processes that can be accommodated in SELECT. Although different population projections and assumptions led to divergent outcomes, urban land development is not a linear product of population change but the result of complex relationships between population, dynamic urbanization processes, stages of urban development maturity, and feedback mechanisms. These findings highlight the importance of accounting for spatial variations in the population projections, but also urbanization process to accurately project long-term urban land patterns.

1. Introduction

Population growth is a major determinant of natural resource demands and subsequent global environmental change, such as land use and land cover (LULC) change. Over the last few decades, rapid population growth has been a driving force behind substantial changes in LULC (Tong and Qiu 2020). On the other hand, changes in LULC can also induce significant feedbacks on population characteristics. Elevated rates of urbanization may attract immigration from other areas, resulting in compounded population growth (Mulder 2006, Brelsford *et al* 2020, Jones *et al* 2020, Koomen *et al* 2023). Understanding these interdependent relationships helps address sustainability challenges by increasing the realism of urban land projections, based on anticipated shifts in population growth (Gao and O'Neill 2021).

The bilateral relationship between population changes and urban land expansion varies across time, space, and scale and can occasionally be contradictory (Schneider *et al* 2015, Angel *et al* 2016, Güneralp *et al* 2020, Mahtta *et al* 2022). Previous research on population characteristics of urban land change has focused mainly on stratified samples of individual cities (Schneider *et al* 2015, Angel *et al* 2016) or meta-analyses (Güneralp *et al* 2020) at regional or global scales. While this literature has contributed to a broader understanding of modern urbanization, mechanisms driving urbanization can be overgeneralized since many assessments are subject to sampling bias, such as preferential focus on large cities (Gao and O'Neill 2021), even though small cities show the largest population growth rate (U.S. Census Bureau 2023). While retrospective and empirical analyses can yield insights into pathways of development, these studies alone may not provide the flexibility to understand the fundamental characteristics of the association between population change and urban evolution, especially how these may change in the future (Gao and O'Neill 2021). Alternatively, spatially explicit urban land projection models, informed but not limited by empirical data, can capture urban evolution over time in relation to population pressures and feedbacks to explore spatiotemporal patterns of future urban LULC change.

Spatially explicit modeling of future urban land that incorporates population as a driver can be accomplished using multiple approaches or their combination. These approaches vary in the scope and scale of application to project future urban land and include: using simple assumptions between urbanization and population, such as static per-capita coefficients (Goldewijk *et al* 2010), developing locally resolved urban land expansion models based on spatial proximity and suitability, i.e. cellular automata techniques (Li *et al* 2017), or constructing integrated modeling frameworks that are flexible to accommodate broader scenario frameworks, while also emulating localized cellular patterns using a variety of approaches, such as statistical learning techniques (Gao and O'Neill 2019) or machine learning approaches (Chen *et al* 2020). Models that adopt static coefficients show a wide range of uncertainty and frequently ignore significant spatial and temporal variability (Schwanitz 2013), whereas most previous applications of cellular automata techniques provide spatially variant outcomes but have future projections that are highly constrained by past empirical data inputs (Terando *et al* 2014, Zhou *et al* 2019).

Alternatively, data-driven approaches that utilize statistical learning or data mining can take advantage of temporally dynamic empirical datasets of urban land change and its driving forces to project future spatiotemporal patterns of urban changes, i.e. urban evolution, in a way that can accommodate scenarios and shifting socioeconomic conditions. In past years, the absence of global spatial time-series data has limited these approaches. However, in recent years, researchers (e.g. Gao and O'Neill 2019, 2020, Chen *et al* 2020, Gao and Pesaresi 2021a) have taken advantage of recently available, spatially explicit time-series global datasets of built-up land, such as the Global Human Settlement Layer (European Commission 2023), and related socioeconomic and environmental variables to develop new data-driven models that focus on modeling changes, especially long-term urban LULC.

The Spatially Explicit, Long-term, Empirical City developmenT (SELECT) model (Gao and O'Neill 2019) is such a data-driven framework, designed to enable long-term large-scale spatially explicit studies. The SELECT model operates at many spatial scales, each accommodating population inputs, with various design characteristics accounting for local variations in the urbanization process, and flexibility to facilitate scenario-based analysis of global long-term urban land development trends, such as the Shared Socioeconomic Pathways (SSPs). Furthermore, the SELECT model distinguishes regional and local differences in the urbanization rates according to past urbanization maturation, which is crucial for big countries with high regional heterogeneity in demographic processes, such as the United States (US).

Here we simulate different future urban land projections at 1 km in the conterminous United States (CONUS) using the SELECT model based on two alternative spatially explicit population projections, one created from state-specific (SP) assumptions of fertility, mortality, and migration, and the other created from national-level projections (NP), which have a single set of demographic parameters for the entire country. We examine how the different assumptions of population changes, in conjunction with regionally and temporally dynamic drivers of urban built-up trajectories affect urban land changes under the same global SSPs. To be clear, our experiment examines the influence of divergent population assumptions within rather than among SSPs, as local extensions of SSPs may lead to variable results based on geographic and socioeconomic contexts (Absar and Preston 2015). Additionally, we sought to understand how urban intensification and extensification differs among existing built-up areas and rural areas, respectively, depending on the nature of population growth and urban maturity.

2. Materials and methods

2.1. Background and experimental design

The urban land projection model used in our study, SELECT, estimates the fraction of urban land within

1/8° grid cells using spatial population data as an input among other socioeconomic and environmental variables (Gao and O'Neill 2019). Since SELECT was empirically calibrated using the Global Human Settlement Layer (GHSL), it follows the same definition of urban land as synonymous with impervious surfaces, i.e. manmade materials such as cement and asphalt (Gao and O'Neill 2019). However, it should be noted that impervious surfaces have been formally differentiated from other definitions of 'urban land', such as built-up areas (dense settlements) or jurisdictional boundaries (Liu *et al* 2014). SELECT is a temporally dynamic model where future urban land projections are, in part, an outcome of population forcings, but also past urban trajectories and urban maturity, environmental constraints, and spatially dependent processes that govern urban land expansion at both regional and local levels.

SELECT consists of two sub-models, a spatial built-up land change model and a sub-national spatial allocation algorithm, which, respectively, estimate land development potentials at the grid scale and allocate the national total amount of new land development for each decade to subregions and then to grid cells. Additionally, SELECT is typically constrained by the Country-Level Urban Building Scenario (CLUBS) model, which estimates national urban land totals according to macroscale socioeconomic patterns and each country's urbanization trajectory and maturity. Population inputs are interjected within all three of these model or sub-model environments. First, dynamic future changes in population and socioeconomic variables are incorporated as predictor variables into CLUBS, a Generalized Linear Model, to estimate national totals of urban land. Second, at the local level, each grid-cell's potential for urbanization change is determined at the beginning of each decade by the built-up land change model, comprised of a quadratic general trend model, and a locally dynamic model. The general trend model predicts the current rate of urbanization based on a grid cell's urban maturity or, alternatively, the cell's current level of urbanization (Gao and O'Neill 2019). At low urbanization levels, urbanization is rapid in these cells, whereas at high mature urban levels, urbanization slows. Locally dynamic models are Generalized Additive Models developed separately for each subnational region ($n = 20$ for the US) where temporally dynamic urban growth potential for each decade is dependent on non-linear relationships with three different time-variant measures of population size and rate of change, environmental variables, and spatial autocorrelative surrogates of land-development controls (Gao and O'Neill 2019). Third, the sub-national spatial allocation algorithm assigns national totals to each subregion for each decade, weighted by population size at each time-step and urban land in the base year. Hence, within the SELECT model, population imposes direct effects on urbanization by influencing the propensity of urban land change at multiple scales while also indirectly influencing the nature of urbanization via feedbacks in previous time-steps, which can shift the future evolution and trajectory of subsequent urbanization. In summary, urban land projections in our model experiment are not linear extrapolations of population, but rather, the result of complex interactions between population and spatiotemporal urbanization dynamics.

Our experiment used two very different population estimates as inputs to the SELECT model. NP projections utilized country-specific population totals previously produced for each SSP and explicitly accounting for fertility and international migration consistent with global SSP narratives (O'Niell *et al* 2017, Samir and Lutz 2017). Using an empirically calibrated gravity-based model (Jones and O'Neill 2013), Jones and O'Neill (2016) downscaled these national totals into 1/8° grid cells of 'urban' and 'rural' populations, which are differentiated based on parameters reflecting different spatial patterns, including the affinity, or lack thereof, to existing urbanized areas and parameters governing the propensity to experience growth based on current population levels. Parameters governing the spatial organization of downscaled population estimates vary among regions and according to SSPs. For the NP projections, these parameters are determined at the country-level. In contrast, parameters in the SP projections are based on state-specific assumptions (Jiang *et al* 2020), although the SP projections, when aggregated to entire US, are compatible, although slightly lower, than the NP population totals. Zoraghein and O'Neill (2020b) downscaled SP projections from states to 1 km gridded resolution.

As described by Jiang *et al* (2020) and Zoraghein and O'Neill (2020b), the SP projections differ from the NP projections in three major ways. First, in the SP projections, more recent baseline data on population demographics, fertility, mortality, and international migration are used, which influences the future projections. Second, the NP projections assume that international migration across all SSPs will decline to 0 after 2050, purely due to uncertainties beyond mid-century. In contrast, net immigration rates in the SP remain constant through the end of century, except for SSP3 (regional rivalry), where immigration declines to 0 post 2050. Finally, the NP projections do not include any assumptions on domestic or bilateral migration among states, whereas the SP maintain consistency between international and domestic migration rates. In this case, bilateral migration rates remain constant in SSP2, double in SSP5, and decline by 50% in SSP3. In both

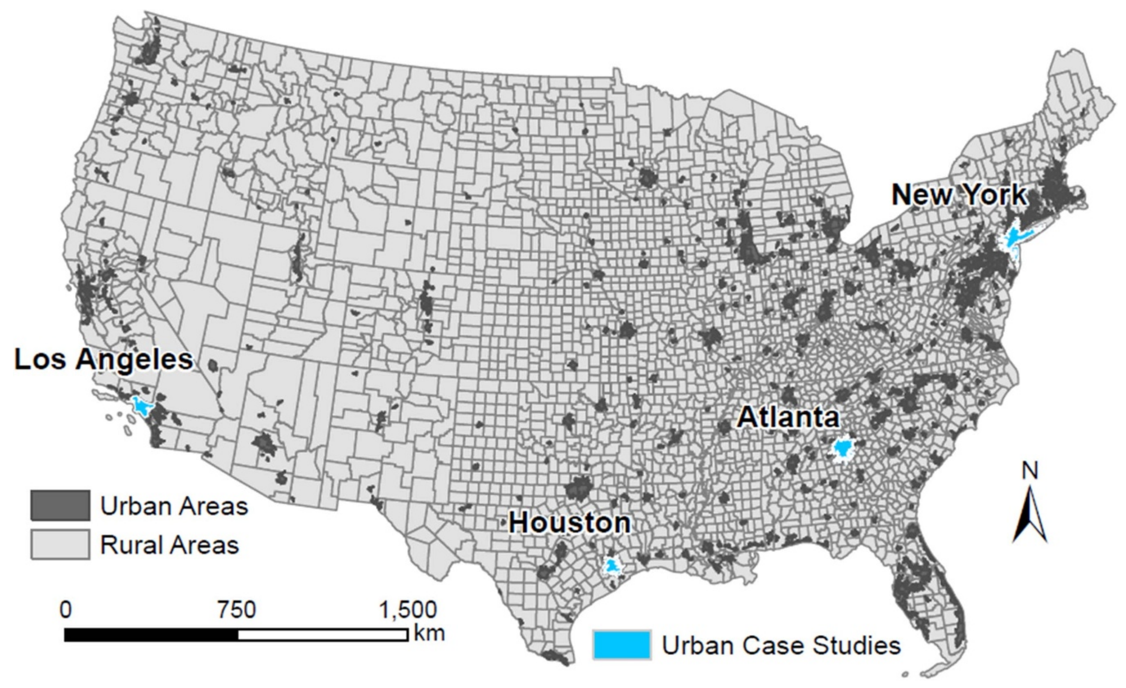

Figure 1. Map of urban and rural areas for the conterminous US, along with urban case studies.

the NP and SP projections, country or state estimates, respectively, were downscaled to gridded values using an empirically calibrated gravity-based model, originally described by Jones and O'Neill (2013). Downscaled NP gridded population estimates are described by Jones and O'Neill (2016) whereas state-specific totals downscaled to gridded values are described by Zoraghein and O'Neill (2020b).

We designed a clear experimental test of the influence of shifting spatial distributions of population on urban land expansion by constraining total urban land in the US (at a national level) to be consistent within each of three SSPs (2, 3, and 5). In our experiment, we kept national totals for each SSP from CLUBS constant among the two population scenarios. By doing so, we can explicitly test how shifting population dynamics, specifically fertility, mortality, and migration, will influence the spatial distribution of urban intensification and extensification. In this case, population can influence urbanization at both the cellular level, based on the locally dynamic model and feedbacks via the general trend model, and at sub-national level, via urban land allocation within the sub-national spatial allocation algorithm.

2.2. Defining 'Urban/Rural' areas

Urban land expansion can adopt two divergent styles: intensification or infilling in existing built-up areas proximate to cities, or extensification into areas currently defined as 'rural'. In this study, we separate existing urban and rural areas of the US to differentiate patterns of urban intensification from extensification between the population scenarios. Defining urban and rural 'areas' has been accomplished under numerous approaches (e.g. Goodall *et al* 1998, Parks *et al* 2003, Hall *et al* 2006, Zhao *et al* 2019, Schroeder and Pacas 2021, Danek *et al* 2022). In this study, 'urban areas', as defined by the US Census Bureau, are areas with 50 000 or more people, which most accurately resembles a compromise between urban 'jurisdictional areas' and 'built-up areas' as defined by Liu *et al* (2014) (figure 1). Rural areas, then are the remaining geographic areas that are not urban (McManamay *et al* 2022a, Mulrooney *et al* 2023) (figure 1).

SELECT simulations can result in grid cells in both urban and rural areas having urban land fraction values >0. We aggregated total urban land within urban and rural area boundaries to reflect urban intensification versus extensification, respectively. Using fixed urban and rural boundaries to account for new land development over time allows for standardized comparisons and assessments of urban land change patterns and trends across different time periods. However, one limitation of this approach is that it fails to formally evaluate transition zones and gradation in urbanization patterns.

2.3. Model simulation and analysis

The NP population data, described by Jones and O'Neill (2016), are available as 1/8° gridded data (Jones and O'Neill 2020), and subsequently downscaled to 1 km by Gao (2020) (figures 2(a)–(c)). The SP population data, based on state-specific

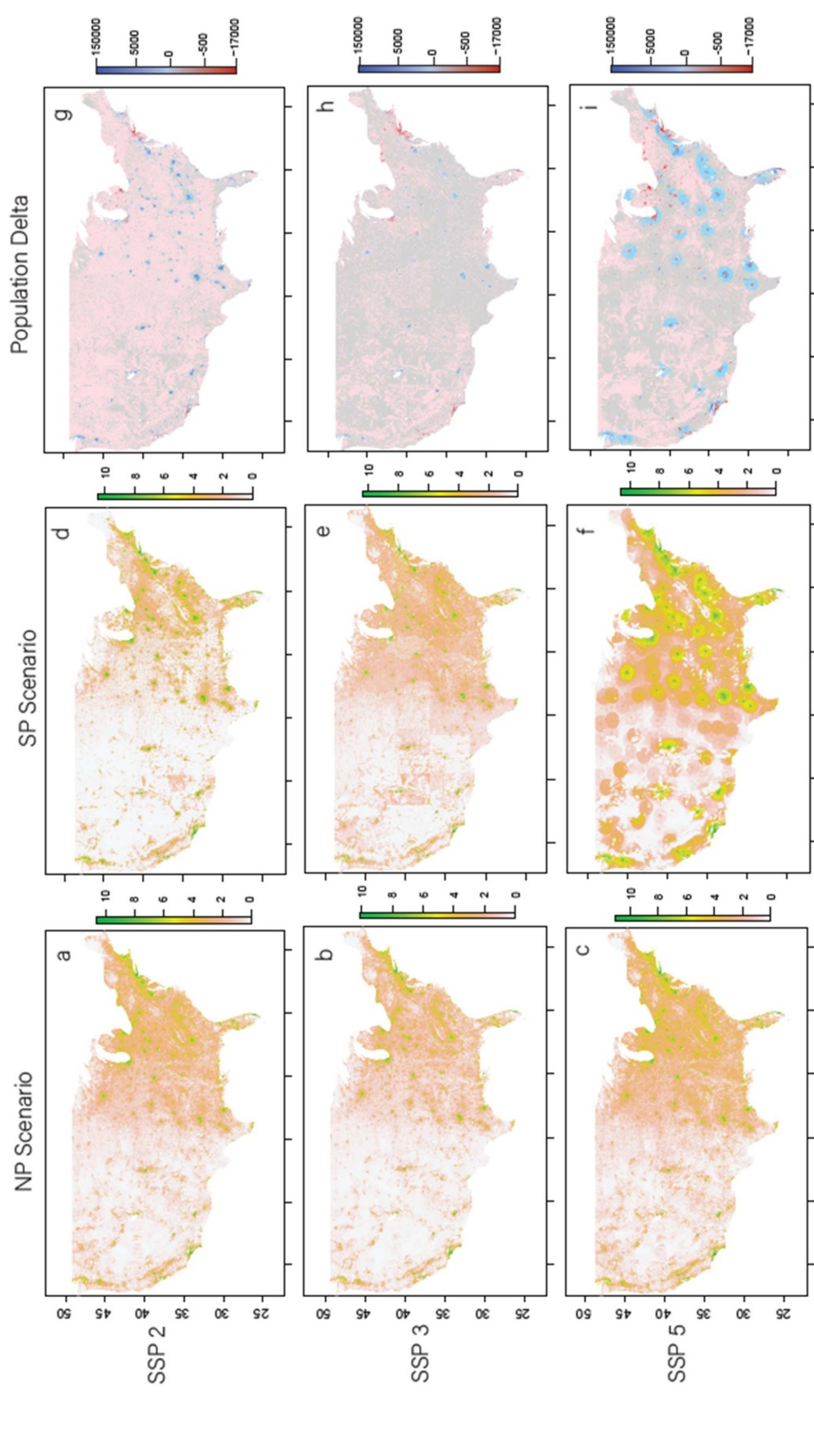

Figure 2. Total population in 2100 based on the national-level (NP) projections (a)–(c), state-specific (SP) projections (d)–(f), and population delta values (g)–(i) for the conterminous US among different Shared Socioeconomic Pathways (SSPs). NP and SP projections were obtained from Gao (2020) and Zoraghein and O'Neill (2020b), respectively.

projections for the US (Jiang et al 2020), are described by Zoraghein and O'Neill (2020b), and available as 1 km gridded data (Zoraghein and O'Neill 2020a) (figures 2(d)–(f)). Because the native resolution of SELECT is at 1/8°, all population datasets were aggregated from 1 km to that resolution. Using the SELECT model, we then simulated urban land fraction using the using the NP and SP population projections at 1/8th degree for every decade from 2010 to 2100. Using a spatial scaling algorithm (Gao and Pesaresi 2021b), urban land fractions were subsequently downscaled to 1-km gridded outputs. The output from these simulations includes decadal estimates (2010–2100) in urban land fractions at 1 km for the conterminous US under SSPs 2, 3, and 5 and are freely available on the U.S. Department of Energy MSD Live Data Repository (McManamay et al 2022b).

Urban land fractions were converted to urban land area (km^2) per 1-km grid cell. Differences in urban land areas arising from the population assumptions were summarized for each grid cell using an urban land delta (ULD) metric. ULD was calculated by subtracting urban land area estimated using the NP population inputs from the SP population inputs. ULDs were calculated for each for each SSP (SSP2, SSP3, and SSP5) for every time-step from 2010 to 2100 to determine differences in temporal behaviors in reaction to the different population assumptions. Urban land area estimates for both population projections and the ULD values were summarized in the urban and rural areas of the US, as defined in the previous section. ULD values from 2010 to 2100 were normalized ($\overline{\text{ULD}}$) from -1 to 1 for each urban and rural area for each SSP using the following equation:

$$\overline{\text{ULD}} = \frac{\text{ULD}_{ikt}}{\max\left(|\text{ULD}_{ik}|\right)\forall t}$$

where ULD values for urban or rural area i, and SSP k, and the t decadal time step are normalized by the maximum absolute value across all time steps. We used Ward's hierarchical agglomerative clustering in R 4.2.1 (R Development Core Team 2022) to identify temporally variant clusters of ULD behaviors in urban and rural areas based on Euclidean distances. Dendograms were visually inspected to qualitatively determine the most parsimonious tree sizes where variation between groups was maximized. Clustering was conducted separately for each SSP and for urban and rural areas. Average temporal trends in ULD among clusters were generalized using a loess smoothing function and visualized for comparison with the spatial distribution of clusters. We selected four metropolitan areas (New York, Atlanta, Houston, and Los Angeles) to compare temporal trends in ULD values for each urban area and its respective rural area under the three SSPs.

We questioned whether differences in urban land outcomes were an artifact of the boundary conditions arising from the architecture of the population projections or that of the SELECT model (see Supplemental Data). Additionally, to directly explore the relationship between population and urbanization outcomes, we calculated a population delta, as the difference in population between the SP and NP scenarios, for each urban and rural area, and compared these values to the ULD for the same areas. We plotted these values according to urban and rural areas, SSP, and year.

3. Results

We projected urban land fraction and area at 1 km for the period 2010–2100 in both urban and rural areas for the conterminous US under three SSPs, each with two population projections. Population projections showed the most divergence for SSP5, then SSP2, and least difference for SSP3 (figures 2(g)–(i)). Total urban land in the CONUS remained virtually identical between the two population projections, as was expected given that total urban land was constrained at the national level. Consistent with SSP narratives, urban land growth is greatest in SSP5, followed by SSP2, and then SSP3 (figure 3). Under all SSPs and both population projections, urban land is expected to increase in both urban and rural areas until the end of the century (figure 3). Most of this growth is expected to be sprawl occurring in areas currently characterized as rural, where urban land is expected to see 1–7-fold increases by 2100 (increases of 39 000–373 000 km^2) (figures 3(c) and (d)). Current urban areas are expected to see only 0.1–0.7-fold increases (11 000–58 000 km^2 of growth) (figures 3(a) and (b)). These results are essential to keep in consideration when appropriately interpreting differences in population projections.

Urban land estimates across the entire conterminous US were similar for both urban and rural areas between the NP and SP population projections, except in SSP5 where urban land in urban areas shows a noticeable departure post-2040 (decline from NP projections) (figure 3(a)). This decline in urban areas is mirrored by a slight increase in urban lands in rural areas starting in 2040 and becoming increasingly apparent by the end of century (figure 3(c)). Percent changes in urban land among population projections remain within -1% to 1% for both urban areas and rural areas except for SSP5, which depicts noticeably lower urban lands in urban areas and noticeably higher urban land growth in rural areas between the population projections (figures 3(b) and (d)).

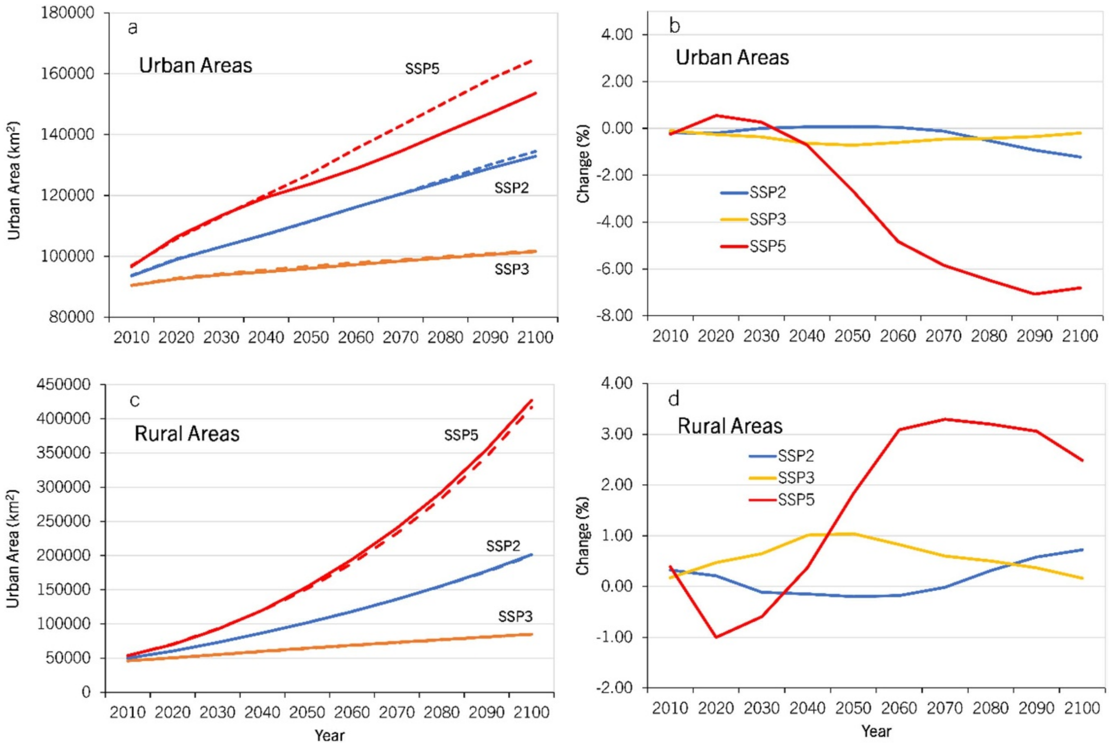

Figure 3. Total urban land area in both current urban (a) and rural (c) areas of the conterminous U.S. projected by SELECT under each Shared Socioeconomic Pathway (SSP). Simulations of urban land were compared using state-specific population projections (solid lines) and the national-level population projections (dashed lines). Percent changes in urban land area (state-specific relative to national-level) for reach SSP in urban (b) and rural (d) areas (right panels).

Urban land simulations at 1 km across the US appeared relatively similar between the NP and SP population projections when viewed at the entire US (figures 4(a)–(f)); however, the geographic distribution of ULD values varied dramatically according to the SSPs (figures 4(g)–(i)). The distribution of ULD values indicated that some regions are areas of stronger divergence in expected urbanization based on differences in population projections, although patterns suggestions that areas within the same US region or even state could experience very divergent ULD values. Examples comparing future urban land simulations arising from alternative population projections are provided for two cities, Atlanta and Los Angeles (figure 5). Population projections clearly show clear differences, even with SSPs; however, differences in urban land vary depending on each city's context (figure 5).

We converted ULD values to percent changes to compare urban land estimates under the SP projection to that of the NP projection, where ULD is divided by urban land under the NP projection multiplied by 100. Percent ULD changes for all SSPs ranged widely across urban and rural areas (figure 6). Under SP projections in 2100, urban areas had anywhere from 96% lower urban land to 14-fold increases in urban land compared to NP projections, depending on location (figures 6(a), (c) and (e)). Likewise, rural areas under SP projections for 2100 experienced anywhere from 100% lower urban land area to almost 300-fold increases in urban lands compared to NP projections (figures 6(b), (d) and (f)). Although differences in urban lands from population projections were more extreme for SSP5, all SSPs showed significant changes for urban and rural areas. In SSP2, changes in urban areas were positive within the southern US but negative in north central and northeastern urban areas (figure 6). Rural areas in SSP2 experienced decreases in the eastern central regions but primarily increases elsewhere. Percent changes in SSP3 were less extreme with very few changes observed in urban areas, but more noticeable changes in rural areas, where increases were observed in the northern West, decreases in the Southwest, and mixed responses in Texas and the central US (figure 6). Under SSP5, the magnitude of changes was stronger than the other SSPs but occurring in patches of urban and rural areas. Rural areas experiencing increases in ULD were more apparent and abundant in SSP5 and broadly scattered across the US (figure 6).

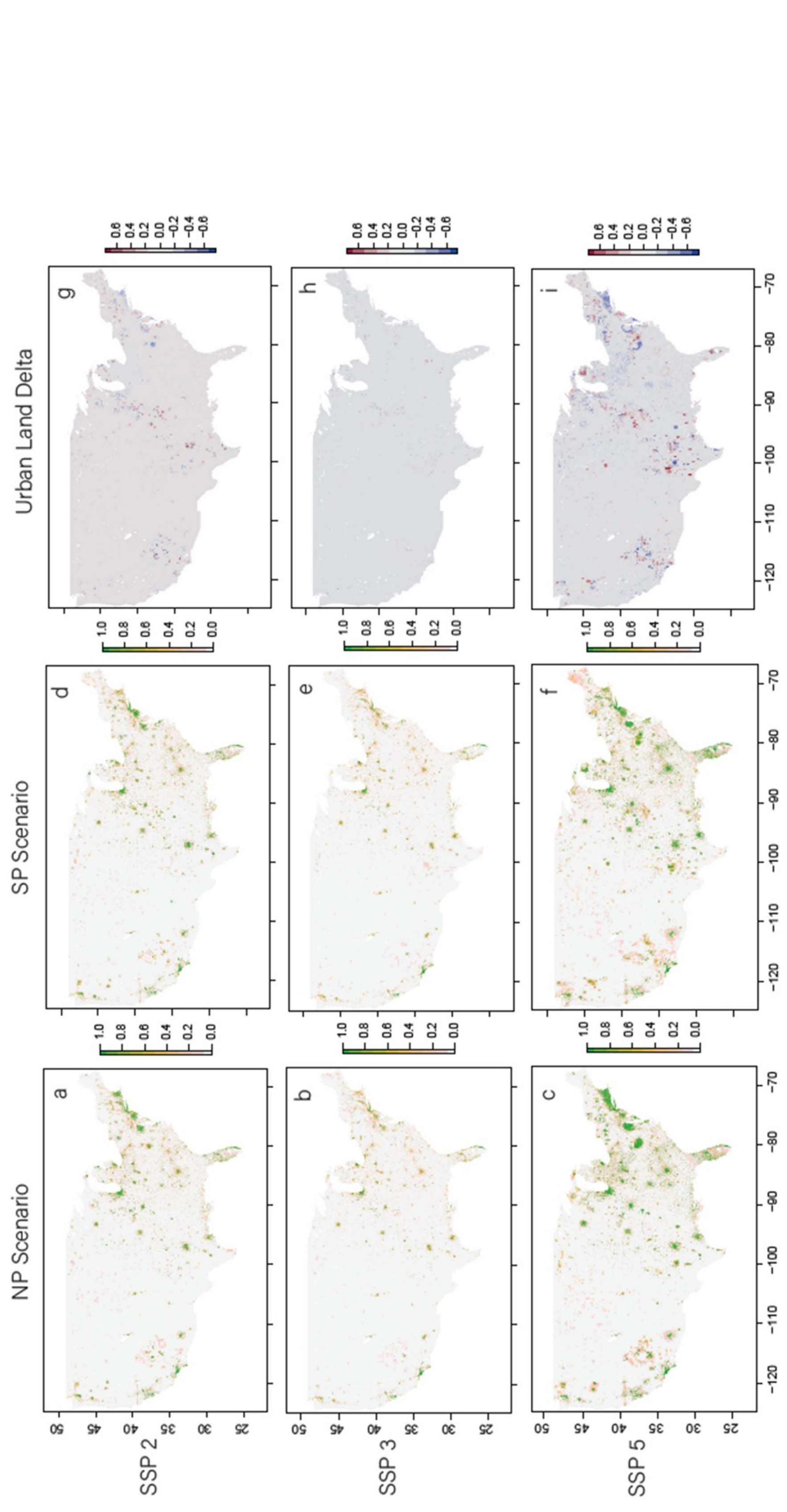

Figure 4. Urban land fraction in 2100 based on the national-level population (NP) projections (a)–(c), state-specific (SP) population projections (d)–(f), and urban land delta values (h)–(j) for the conterminous US among different Shared Socioeconomic Pathways (SSPs).

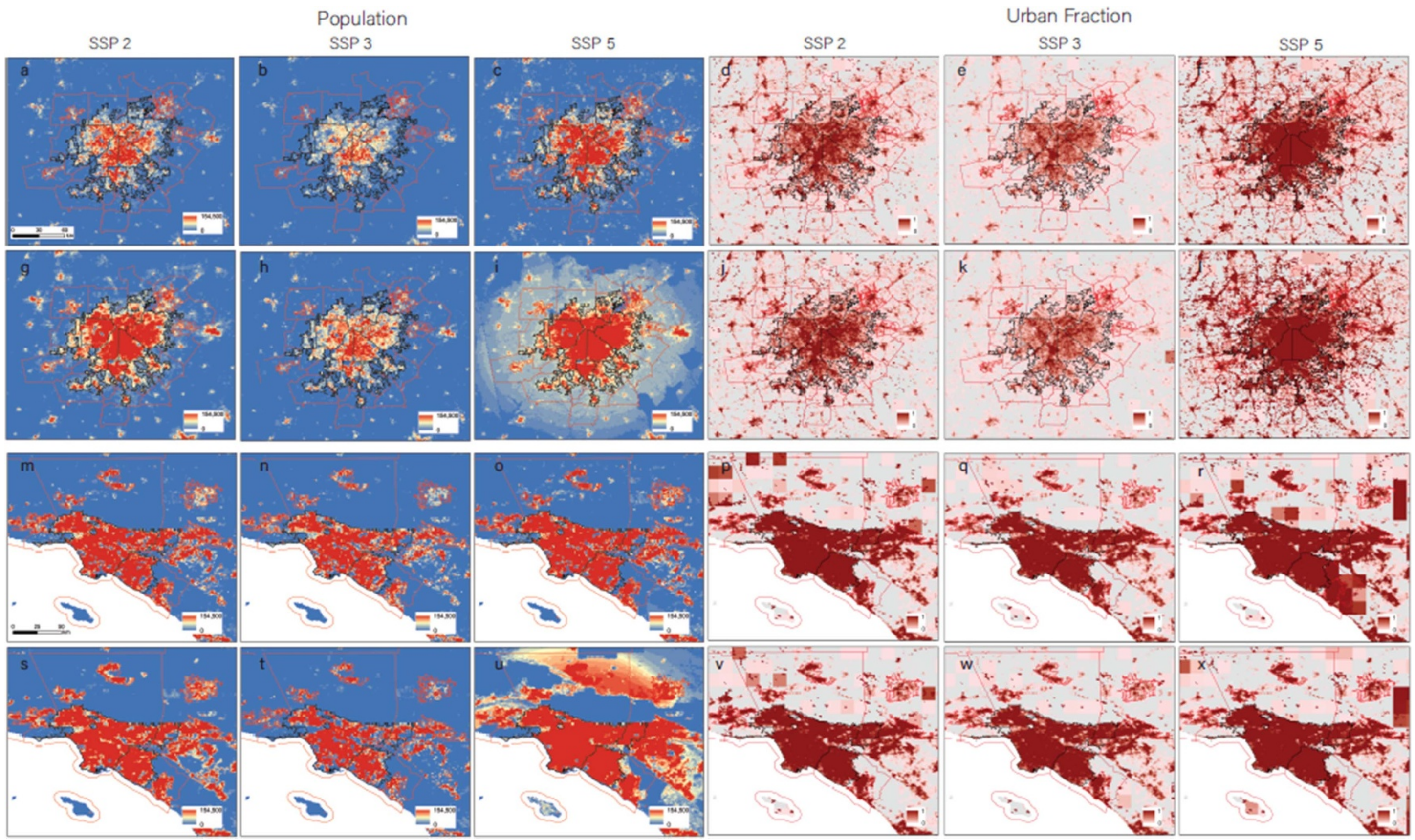

Figure 5. Examples of national-level population projections (a)–(c), (m)–(o) and state-level population projections (g)–(i), (s)–(u) for Atlanta, Georgia and Los Angeles, California, respectively, across the Shared Socioeconomic Pathways (SSP) 2, 3, and 5. Urban land fractions were simulated by the SELECT model using the NP projections (d)–(f), (p)–(r), and the SP projections (j)–(l), (v)–(x).

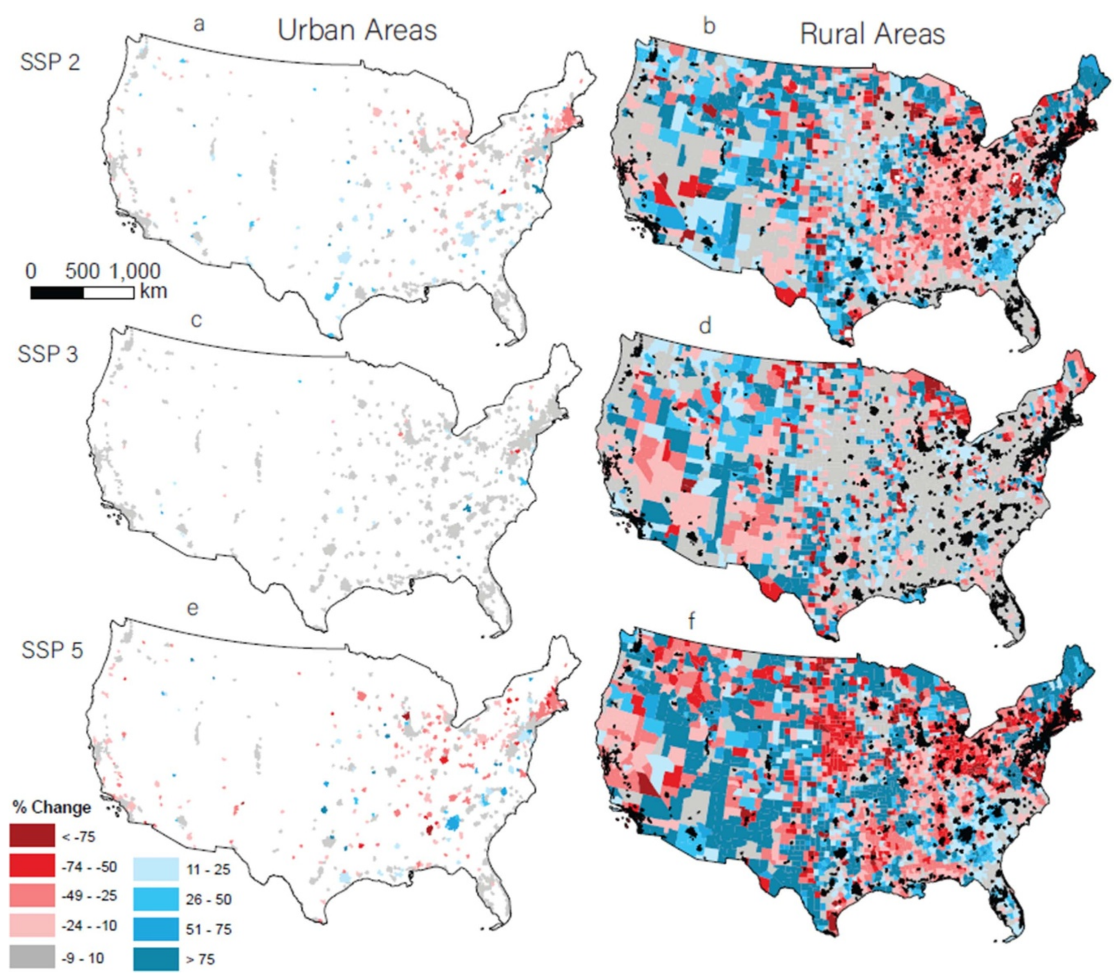

Figure 6. Percent changes in urban land area by 2100 based on state-specific relative to national-level population trajectories for each Shared Socioeconomic Pathway (SSP) in urban (a), (c), (e) and rural areas (b), (d), (f). Urban areas are shown in black in maps of rural areas.

3.1. Spatial clustering of urbanization under different SSPs

To condense spatiotemporally complex patterns in urbanization between the population scenarios, we developed clusters of ULD changes to represent typologies of temporal 'behaviors' under different SSPs (figures 7 and 8). We found that five clusters tended to provide a balance between parsimony and capturing the most variation in patterns across all SSPs for both urban and rural areas. Cluster assignment displayed some geographic affiliation; however, assignment was not uniform for regions or states (figures 7 and 8). SSP5 displayed the least regional uniformity in ULD cluster assignments. Cluster groupings also varied individually for rural and urban areas under SSPs. For instance, regional uniformity seemed more apparent under SSP3, whereas in SSP5 urban areas in close proximity were highly heterogeneous and assigned to divergent clusters (figures 7 and 8).

Urban areas displayed highly divergent increasing, decreasing, or variable ULD values over time (figure 7). Under all SSPs, urban areas in the Northeast and California had increasingly negative ULDs, except for New York which showed the exact opposite pattern (figure 7). Urban areas in the Southeast and South-Central US generally displayed increasing ULD, except areas in the gulf and Florida, which were mixed. Other urban areas of the US showed both positive and negative ULD values, depending on the SSP.

Likewise, ULD values for rural areas were also variable, displaying some level of geographical affiliation in SSP2 and SSP5 (figure 8). For instance, the East-Central US and gulf regions were predominantly negative ULD values under SSP2, yet most of the remaining US displayed positive values. Despite some geographical affiliation in SSP2 and SSP5, rural areas occurring in the same regions still displayed highly

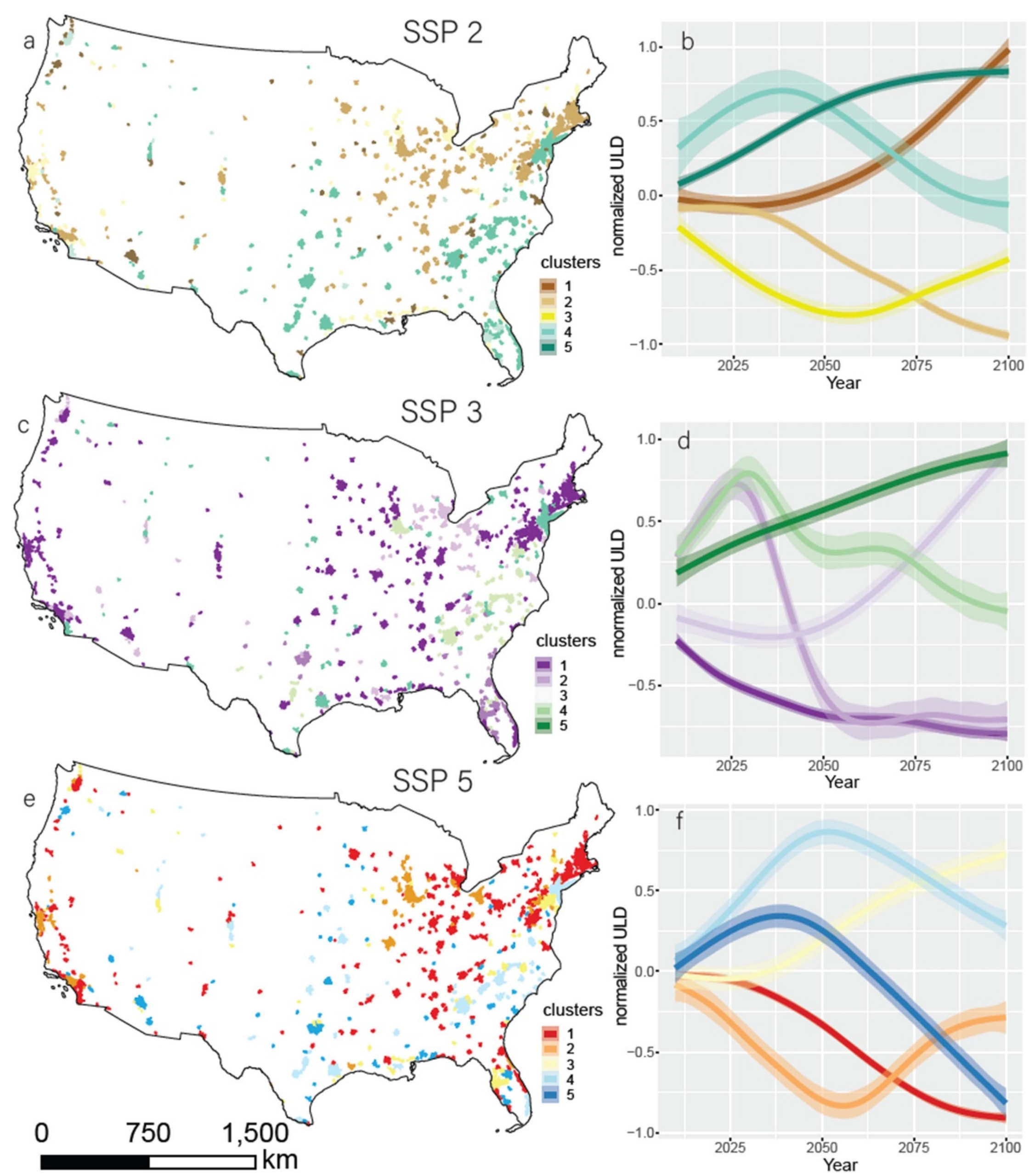

Figure 7. Clusters of urban areas based on temporal behaviors in urban land delta (difference in urban land area simulated using state-specific versus national-level population projections) from 2010 to 2100 under different Shared Socioeconomic Pathways (SSPs), including SSP2 (a), (b), SSP3 (c), (d), and SSP5 (e), (f). Trends show averaged or smoothed conditions for each cluster.

divergent patterns. SSP3 displayed the most spatial heterogeneity in ULD patterns. Under SSP2, most rural areas in the US displayed increasingly positive ULD values; however, the exact opposite pattern was observed in rural areas under SSP3 (figure 8). Rural areas in the US equally displayed divergent pattern of increases and decreases under SSP5.

We found significant differences in urbanization across each city's urban and rural areas between the two population projections (figure 9). The most significant differences in ULD were found under SSP5, followed by SSP2. Urban areas in Atlanta, Houston, and New York displayed increasingly positive ULD values under all SSPs, albeit variable, whereas the directionality of ULD in rural areas surrounding each city were highly divergent (figure 9). Los Angeles displayed the most divergent pattern from other cities, with consistent but negative ULD values in urban areas and positive ULD values in rural areas.

We did not find any consistent relationships between percent changes in ULD and geographic boundaries (Supplemental Data). Linear relationships between the population delta values and ULD were also not observed (Supplemental Data). There were equal numbers of instances where positive population delta values (higher population in SP than NP projections) were associated with negative ULD

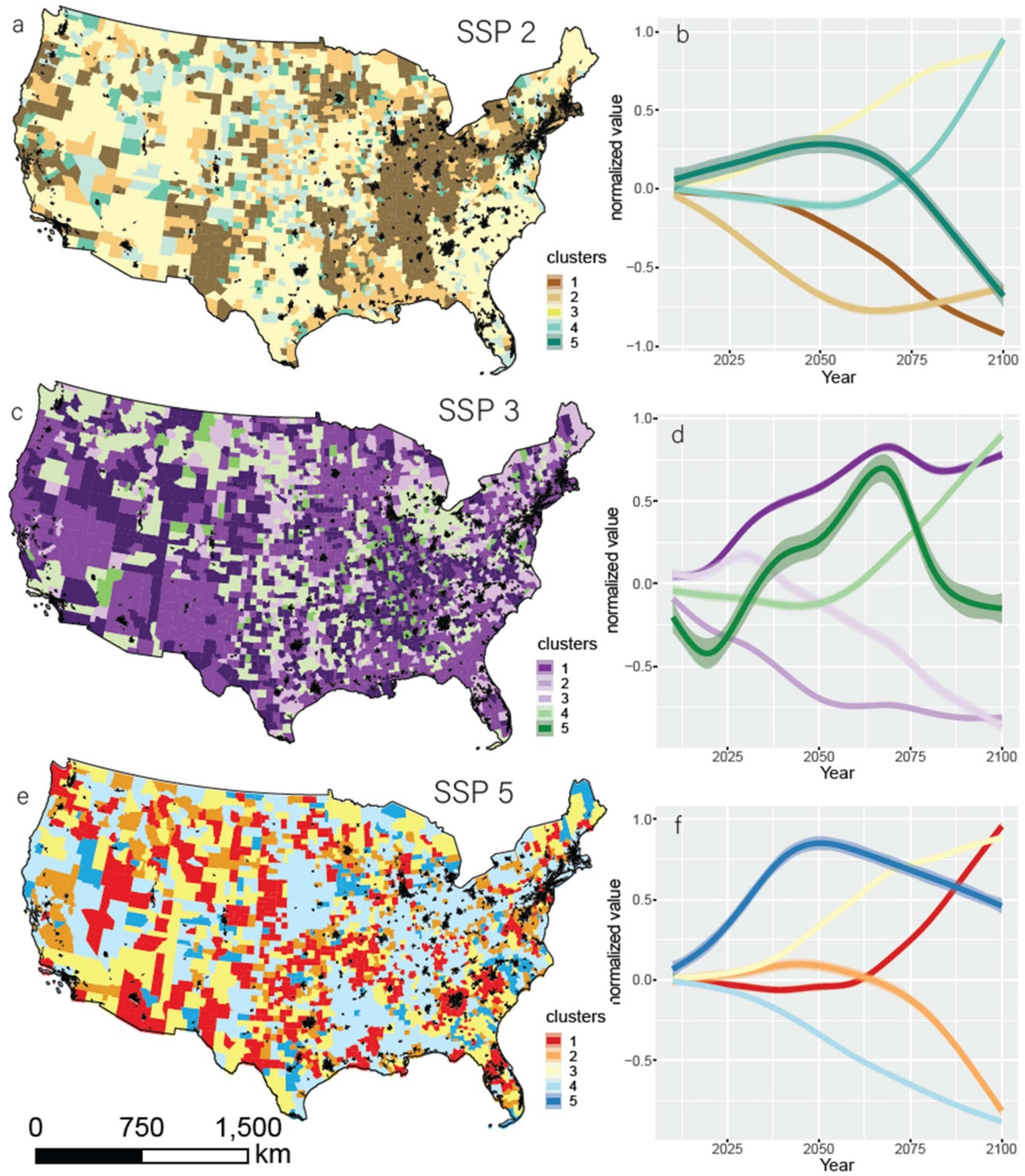

Figure 8. Clusters of rural areas based on temporal behaviors in urban land delta (difference in urban land area simulated using state-specific versus national-level population projections) from 2010 to 2100 under different Shared Socioeconomic Pathways (SSPs), including SSP2 (a)–(b), SSP3 (c), (d), and SSP5 (e), (f). Trends show averaged or smoothed conditions for each cluster.

values (less urbanization in SP projection than NP projection) (Supplemental Data). Likewise, lower population in the SP projection (negative population delta) also led to positive ULD values in many cases. This suggests that urban land simulations were complex and not just simple artifacts of population inputs.

4. Discussion

Our study shows that the distribution of urban landcover can vary dramatically according to different population projection inputs, even under the static boundary conditions of individual global, and even national-level, SSPs. These results highlight the importance of understanding extensions of the SSPs from national to local levels, where the geographical and sociopolitical context becomes increasingly important in influencing simulated outcomes (Absar and Preston 2015). In our experiment, the total urban land budget in the US per year was held constant, yet the spatial distribution of urban land changes was subject to the variability in population inputs. Our results suggest population inputs induce substantial differences in urbanization emerging locally, ranging from 100% lower urban land area to 14- and 300-fold increases in urban land in existing urban and rural areas, respectively.

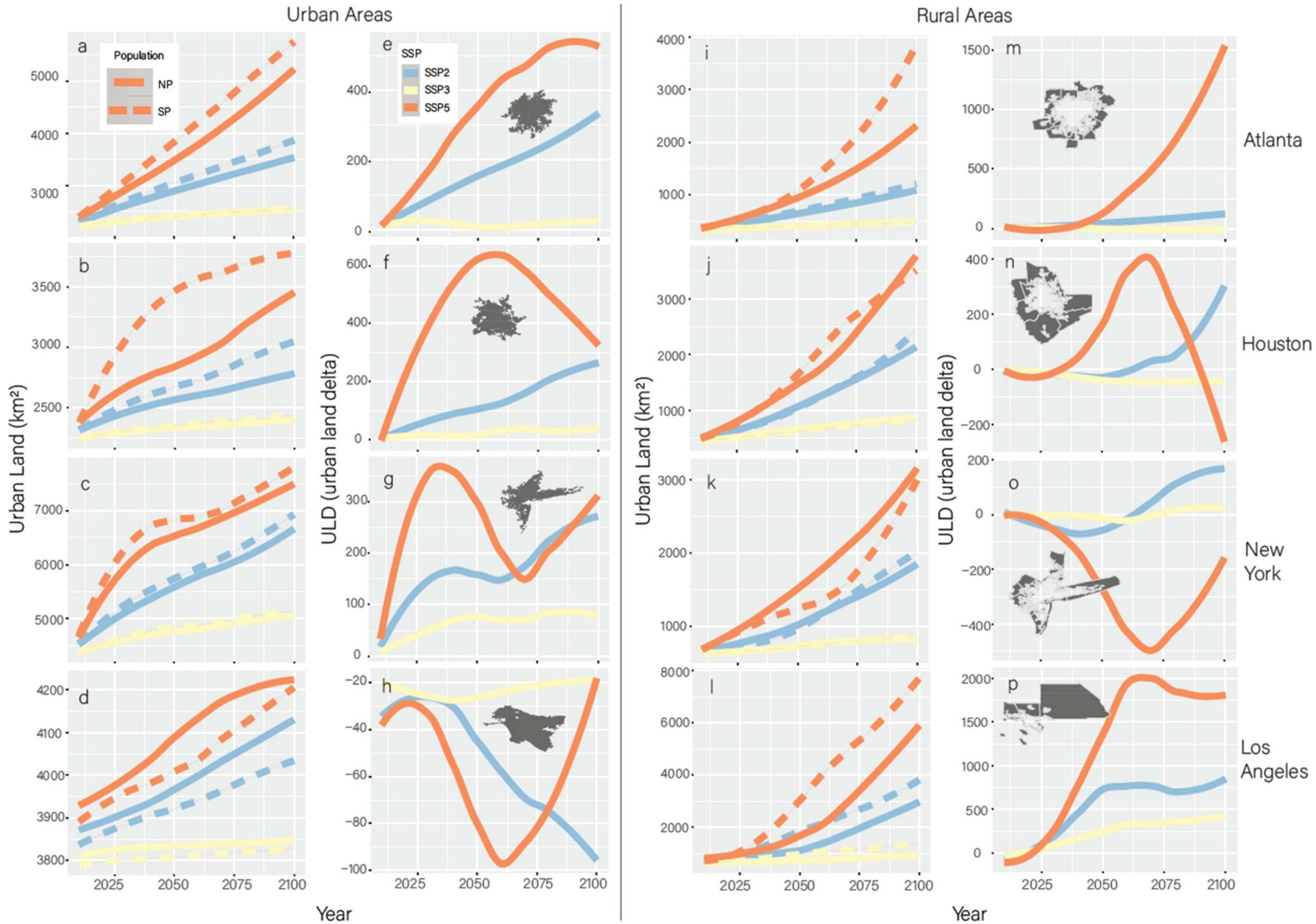

Figure 9. Trends in urban land and urban land delta (difference in urban land area simulated using state-specific versus national-level population projections) from 2010 to 2100 for individual cities (urban areas) (a)–(h) and their respective rural areas (i)–(p) under different Shared Socioeconomic Pathways (SSPs).

Under both population projections, we show that urban land continues to increase at various levels in accordance with differences amongst the SSPs, and our findings are consistent with numerous studies (Li *et al* 2019, Chen *et al* 2020, 2022). Differences in urbanization amongst SSPs are driven by global and national urban land totals, which, in our study, are governed by CLUBs. Scenario SSP5, or fossil-fueled development, displays the highest urban land expansion, followed by SSP2 and SSP3. This is consistent with earlier research (Jiang and O'Neill 2017, Chen *et al* 2020, 2022, Gao and O'Neill 2020), where SSP5 represents a sprawling scenario (Zoraghein and O'Neill 2020b), characterized by rapidly growing populations, expedited globalization caused by material-intensive economic systems, and a lack of concern for the effects on the environment globally, all of which stimulate high rates of urban land extensification. Scenario SSP3, regional rivalry, results in the least amount of urban land development due to slowed-down economic and technological advancements, despite the scenario's predominant material-intensive consumption pattern (Gao and O'Neill 2020). SSP2 represents the 'middle-of-the-road' scenario with more condensed pattern of development, trending toward less lateral dispersal due to moderate levels of economic growth and technological advancement.

We used current, spatially static depictions of urban and rural areas to examine the locality of future urbanization, either infilling or extensification. In both population projections, the total urban land coverage occurring in rural areas will exceed that of urban areas by 2050 in SSP2 and by 2040 in SSP5. Ultimately, this suggests significant urban extensification is expected, regardless of population assumptions. However, rural areas may display disproportionate increases in urban land growth in the state-specific (SP) population projections, 1%–3% higher than that of national-level (NP) projections, depending on the SSP. In comparison, urban lands in existing urban areas are 1%–6% lower in the SP projections compared to NP projections. Increasing the proportion of urban land growth in rural areas suggests an even more extreme form of urban sprawl could predominate, which further increases land stress, perhaps competition over land resources (McManamay *et al* 2022b) and increasing land fragmentation.

The shifts in urban land cover patterns we observed are, in part, due to the assumptions imbedded within the population projections. Population growth is the principal driver of urban land development (Mahtta *et al* 2022), governed by the physical constraints of urban scaling laws (Brelsford *et al* 2020). Indeed, population inputs are universally used and should be considered necessary in future projections of urban land (Jiang and O'Neill 2017, Chen *et al* 2020, 2022). Reia *et al* (2022) show that spatial heterogeneity in population among U.S. metropolitan areas is driven primarily by population flows from domestic migration, not endogenous population growth. Projections of future migration rates in the SP drew heavily upon existing empirical observations, which suggests that contemporary patterns in population growth have higher rural affiliations than previously assumed in the national-level projections. Interestingly, the SP population scenarios utilize trends in domestic migration based on the 2010 US Census Bureau datasets (Jiang *et al* 2020), observed prior to the COVID-19 pandemic. Evidence of the impacts of the COVID-19 pandemic suggest these trends could be strengthened based on housing markets in the US and the United Kingdom where home values in lower-density areas are increasing, leading to decentralizing pressures on the housing market (Gallent and Madeddu 2021, Liu and Su 2021, D'Lima *et al* 2022). This suggests a pattern of more rural-centric urbanizing growth could continue into the foreseeable future, as reported elsewhere (Güneralp *et al* 2020).

Although different population projections were the only variable manipulated in our experimental treatment, our results show that population changes do not necessarily lead to direct or linear responses in urbanization. Differences in population assumptions led to highly divergent and heterogeneous results on urban land growth, even in areas in close spatial proximity. Urban land expansion patterns of four of the US's largest metropolitan regions suggested very diverse responses to different population assumptions, both among cities and among SSPs. For example, extensive urban sprawl observed is expected in low population dense southeastern US cities, such as Atlanta (Terando *et al* 2014). In contrast, Los Angeles has high population densities, with little heterogeneity in the distribution, leading to 'dense sprawl' in urban land development (Eidlin 2005). Ultimately, this leads to little available space for continued urban expansion, resulting in higher population outmigration rates in the SP projection, compared to NP projections.

SP projections displayed more variable urban land trajectories by accommodating domestic migration and more locally dynamic demographic conditions. The cluster analysis of spatiotemporal trends in ULD underscores the non-linearity of urbanization processes to population inputs. Mahtta *et al* (2022) found that on a global scale, population growth is the primary determinant urban land expansion; however, these relationships vary by country. In regions with increasing governance on growth, such as Europe and North America, economics become increasingly influential, at times more so, than population change. Complex inter-dependent relationships between population and urban land development also arise due to spatial interactions. Tong and Qiu (2020) showed that population growth has greater impacts on urban land development in rural areas neighboring urbanized places due to spill-over effects. The authors found that feedback mechanisms induced population growth by attracting suburban and rural residents—this, in turn, results in population declines in neighboring peri urban and rural areas.

We also found no strong and consistent linear associations between population delta and ULD, where 'delta' represents the respective differences between SP and NP projections. Additionally, we did not find evidence that boundary conditions of the model approach led to arbitrary differences in urbanization. Urbanization does not predictably respond to population because of landscape inertia imposed by the nature of urbanization processes and coevolution with multiple drivers, including historical population change. As one example, urban lands do not retract in cases of deurbanizing population change. For instance, Chen *et al* (2011) also showed that the rate of urbanization can either increase or decrease after maturation or saturation. Indeed, population inputs are interjected at multiple levels in the SELECT model. Since we kept total population constant at the national level (i.e. CLUBS), there are only two remaining components in the SELECT model where population could play a role in influencing urban land projections. The first is the sub-national allocation algorithm, which allocates urban land by weighting regions based on population size at each time-step. However, patterns in ULD among neighboring geographic boundaries with similar population sizes was not observed (Supplemental Data), indicating that the subnational allocation unlikely playing a strong role in urbanization patterns. The second component, the locally dynamic model, incorporates dynamic population inputs in a non-linear fashion, where population at previous time-steps can influence the nature and rate of urban land change in each grid cell. Additionally, the locally dynamic model also incorporates local landscape suitability and constraints (e.g. topography, proximity to urban), along with a dynamic decomposition of over 100 heuristic statistics describing urban neighborhood patterns. Our results suggest that these local constraints play more significant role than coarser-scale governing factors, at least in our experiment. Ultimately, capturing the nature of these urbanization processes and evolution through SELECT results in spatially heterogeneous urbanization responses to population inputs. The same population change could lead to very different urban land outcomes in different places. Furthermore, the same population change could also lead to different urban land outcomes at the same location under different time periods.

Although SELECT is empirically grounded and accommodates realistic and dynamic patterns in urban maturation, it is one of many available urban expansion models, each of which display divergent urban land estimates by end of century (e.g. Chen *et al* 2020, Liu and Su 2021). For example, Chen *et al* (2020) estimate anywhere from 125 000–425 000 km^2 of urban land in the US by 2100 depending on SSPs, compared to 185 000–580 000 km^2 under SELECT. Both model frameworks adopt a similar stepwise structure where coarse regression models estimate urban land budgets at national and sub-national levels, which are subsequently allocated to cellular or gridded levels by more resolved dynamic models that account for spatial heterogeneity. Additionally, both models utilize the GHSL as an empirical basis for model calibration. Even so, the models used in each step adopt very different statistical designs, variables, dynamic structure, and parametric uncertainty. CLUBS and SELECT varies from other models in the following major ways: (1) relationships between urban land change and its drivers do not scale linearly and allow for temporal non-stationarity, (2) locally dynamic models are developed separately for 20 sub-national regions within the US, each having their own variables and calibrated parameters, and (3) models are based on variables that best explain historical patterns in urbanization, such as population change and the rate of economic growth, rather than rely on per-capita urban land coefficients or the magnitude of GDP. Gao and O'Neill (2019) previously report validation and parametric uncertainty for the SELECT model, which are manifested at national, regional, and local levels. While our results certainly reflect the choice of model, we believe the urbanization outcomes of our experiment reflect realism in the feedbacks associated with urbanization and the location, timing, and nature of population growth, depending on previous trajectories of growth and urban maturity—this dynamic nature is incorporated into SELECT's structure and naturally influences our results.

In conclusion, our results also show that urban land trajectories can vary dramatically among local scales under the same global 'boundary conditions' of individual SSP scenarios. Divergent urban land patterns at high resolutions highlight the importance of local-specific demographic data, specifically international domestic migration, including linkages among urban and rural populations. As found by Tong and Qiu (2020), our work suggests that urbanization is not a linear outcome of population suggesting the need for more nuanced understanding of the relationships and feedbacks between population and urban land expansion to improve urban land simulation models in the future.

Data and code availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.57931/1887521 (McManamay *et al* 2022b, model simulated output) and https://doi.org/10.57931/2318472 (McManamay *et al* 2024a data for reproducing the analysis). Code for reproducing our analysis is provided at: https://github.com/IMMM-SFA/mcmanamay_etal_2024_erl (McManamay *et al* 2024b).

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