Article

Depopulation and associated challenges for US cities by 2100

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For cities, having a declining population usually means socioeconomic and infrastructure challenges to accommodate the remaining population. Using population projections, we found that, by 2100, close to half of the nearly 30,000 cities in the United States will face some sort of population decline, representing 12–23% of the population of these 30,000 cities and 27–44% of the populated area. The implications of this massive decline in population will bring unprecedented challenges, possibly leading to disruptions in basic services like transit, clean water, electricity and internet access. Simultaneously, increasing population trends in resource-intensive suburban and periurban cities will probably take away access to much needed resources in depopulating areas, further exacerbating their challenges. Although immigration could play a vital role, resource distribution challenges will persist unless a paradigm shift happens away from growth-based planning alone.

In many places in the United States, population decline, or depopulation, has become a demographic reality. According to the US Department of Agriculture (USDA), nonmetropolitan counties accounted for 3.2% of the population loss between 2010 and 2017 (ref. [1]). This population decline in rural United States started long ago[2] and is indicative of an economic shift, which ultimately reduces community well-being and the possibility of a sustainable future[3]. Young adults often migrate out of rural business centers, altering the demographic composition and leaving an aging population in depopulating areas. Nevertheless, rural areas are not alone. After World War II, population decline propagated to city centers, affecting larger cities such as Philadelphia, Detroit and Chicago. These trends were in part due to migration from city centers to suburban areas and from the Northeast/Midwest to Southern cities, coupled with a decline in manufacturing jobs and land-use regulation changes[4]. At the same time, the construction of expressways supported this migration from city to suburbs[5]. Although this decline was happening in many cities, it was not widely recognized before the 1970s (ref. [5]). In 2021, the United States experienced its slowest growth since its foundation[6]. Depopulation, along with aging infrastructure systems, creates social, economic and policy challenges[7]. In particular, population loss in already developed cities can result in underutilized infrastructure with poor maintenance, possibly leading to disruptions in basic services like transit, clean water, electricity and internet access[8,9]. Having an estimation of future population trends can assist authorities in better planning and designing cities and their infrastructure systems for depopulation.

When studying demographic changes such as depopulation, the selection of the geographic unit of analysis matters, as infrastructure planning and developments are zonal processes. In this Article we use organically emerging population agglomerations defined as 'places' by the US Census Bureau[10], hereafter simply referred to as 'cities'. Because infrastructure planning and financing decisions are carried out based on their administrative jurisdictions, we prefer to highlight the extent of the depopulation problem based on a microscopic administrative scale. Here, we investigate three major questions regarding population trends in cities in the United States:

(1) What are the future population trends in all US cities up to 2100—in particular, how many cities are likely to depopulate?
(2) Where are these depopulating cities?
(3) What are the characteristics of these depopulating cities?

This Article can be divided into three sections. First, we identify the current population trend for US cities using US census population data from 2000, 2010 and 2020. Second, we estimate the future trends based on population projection data up to 2100 from two different sources given various climate-change scenarios (defined as shared socioeconomic pathways, SSPs). We inspect how these population trends vary regionally and how they vary across three city characteristics—degree of urbanization, income level and vehicle ownership—because housing
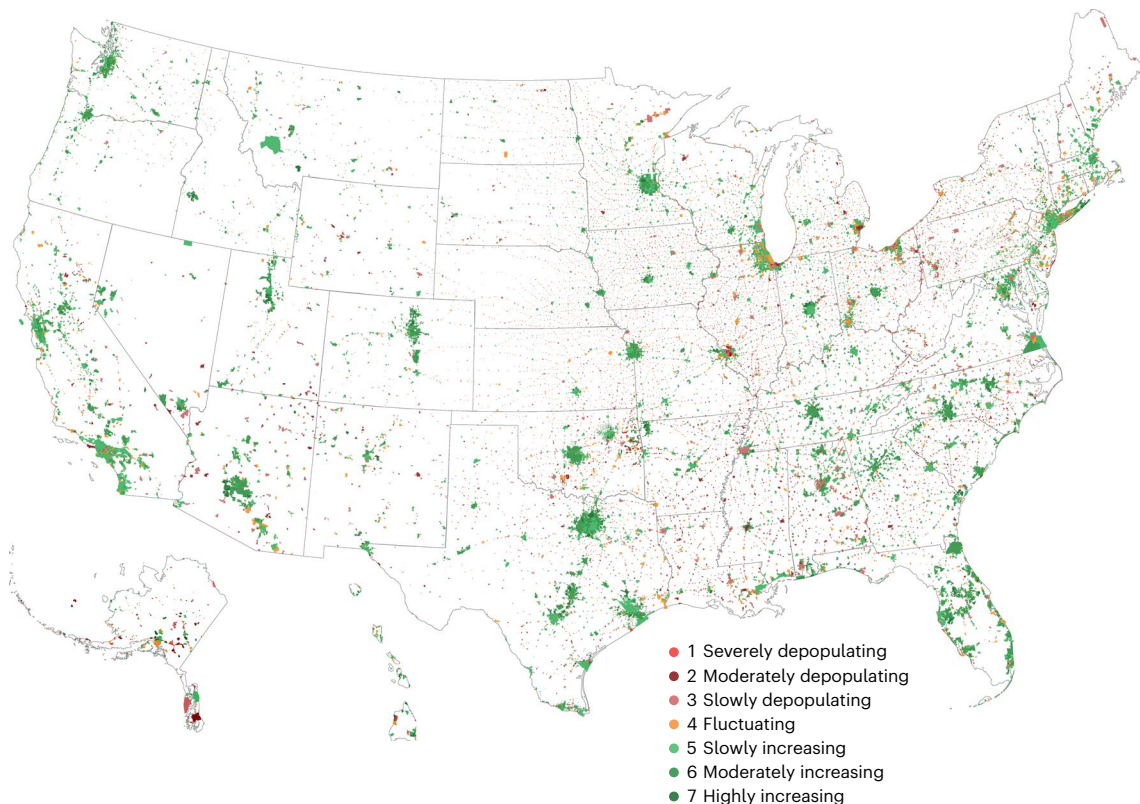
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Fig. 1 | Population trend estimated from US census population data from 2000, 2010 and 2020. Cities that have consistent population data over the past 20 years are included in the analysis. The figure shows that many small cities are depopulating throughout the United States. Major metropolitan centers like Detroit (MI), Cleveland (OH) and St Louis (MO) are experiencing moderate to slow depopulation, while some of the suburban and periurban cities located outside of these centers show an increasing trend. Similarly, in the South, metropolitan centers like Columbus (GA), Birmingham (AL) and Memphis (TN) are losing population, while cities located outside the centers are gaining population.

Legend:
- 1 Severely depopulating
- 2 Moderately depopulating
- 3 Slowly depopulating
- 4 Fluctuating
- 5 Slowly increasing
- 6 Moderately increasing
- 7 Highly increasing

location choice largely depends on income and accessibility[11]. Third, we evaluate the impact of international immigration from 2017–2021 metropolitan statistical area (MSA)-level immigration data to identify the cities that are more likely to compensate for natural population loss through immigration.

Results

Current trends in cities
We divided cities into seven categories using average annual change in population from 2010 to 2020 and the sign of change from 2000 to 2010, 2010 to 2020 and 2000 to 2020 (details are provided in the Methods). These categories address the extent of population loss as well as the direction of population loss over time (increasing/decreasing). The results show that 43% of US cities are losing population, 40% are gaining population, and the remaining 17% show fluctuating trends out of 24,295 cities that have consistent data available for the three time periods (2000, 2010 and 2020).

Figure 1 shows the cities labeled according to their current population trend. Major cities in the Midwest region are slowly losing population. Although cities in the South and West regions are experiencing a population increase, some major cities in Alabama, Georgia and Tennessee are slowly depopulating.

Density variation for these cities, using population data from the 2020 Census and land area from US Census TIGER/Line Shapefiles, shows that severely depopulating cities have a very low population density (Supplementary Information and Supplementary Table 2). Cities labeled as 'slowly depopulating', 'slowly increasing' and 'moderately increasing' range from having a low (~500 people km⁻²) to high (over 8,000 people km⁻²) density. Population density in cities with a highly increasing population is low compared to slowly or moderately increasing cities, which suggests that these cities may be new or have more recently started to attract many people.

Future trends in cities
To estimate future trends, two projected datasets were used to find trends for the 31,568 cities included in the Census Bureau's 2020 TIGER/Line Shapefiles. Both projections consider five scenarios called shared socioeconomic pathways (SSPs) that range from environmentally friendly development (green road) to fossil-fueled development (highway), defined in terms of socioeconomic developments in response to the impacts of climate change. The two datasets are

- Global 1-km Downscaled Population Base Year and Projection Grids Based on the SSPs, v1.01 (2000–2100), referred to as 'NCAR data' hereon[12].
- US County-Level Population Projections, Total and by Sex, Race and Age, based on the SSPs, v1 (2020–2100), referred to as 'Hauer's data' hereon[13].

The NCAR dataset provides a more granular level of detail as it is disaggregated into 1-km grid cells. However, when compared to recent population data, it tends to overweight densely populated cities and underweight sparsely populated ones. In contrast, Hauer's projection is based on more recent population data but at a more aggregated level (county level). When compared to the total 2020 census population for the 50 US states and the District of Columbia, Hauer's data show a slight overprojection, whereas the NCAR dataset shows an underprojection.
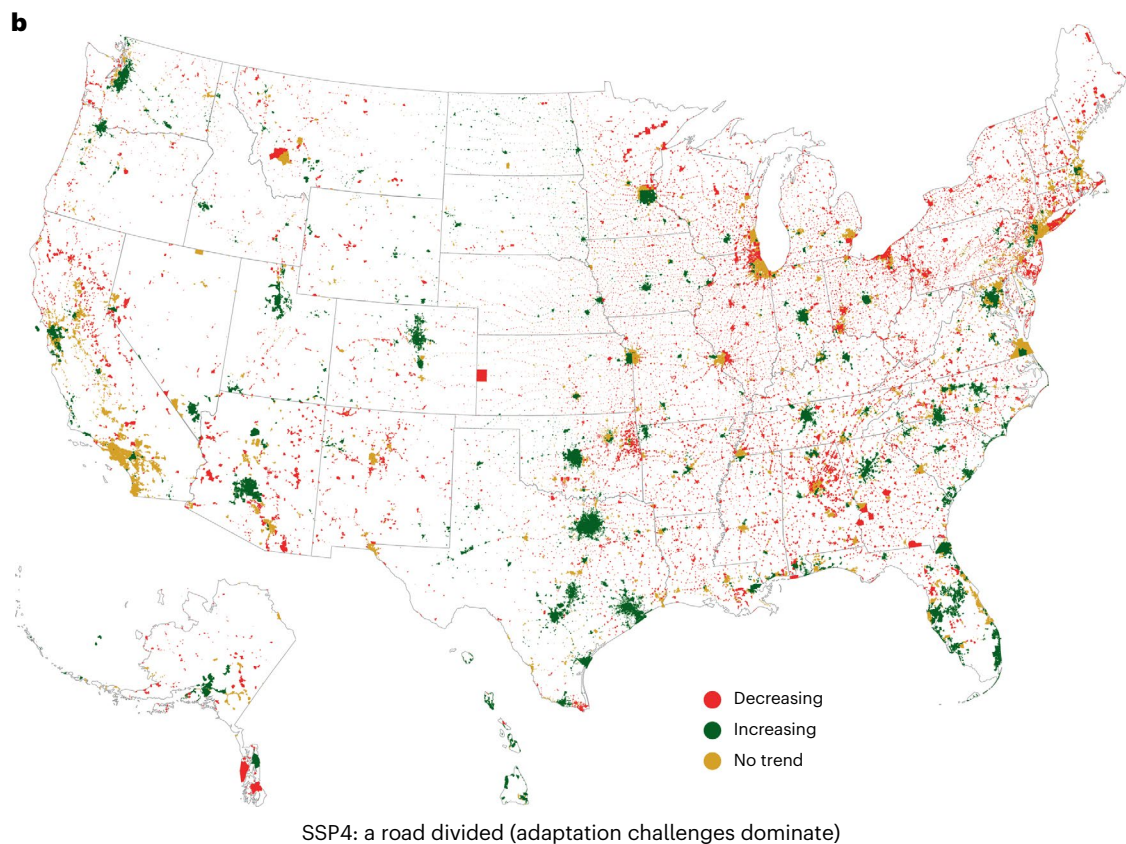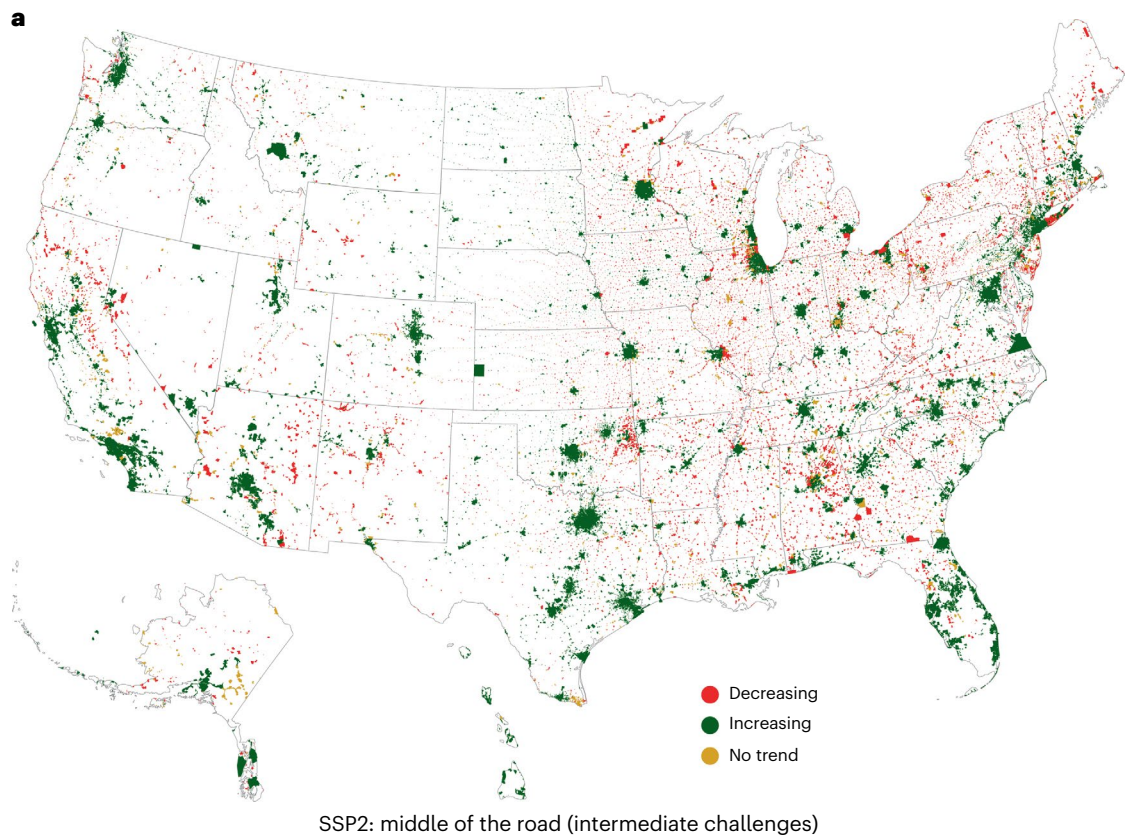
a

SSP2: middle of the road (intermediate challenges)

● Decreasing
● Increasing
● No trend

b

SSP4: a road divided (adaptation challenges dominate)

● Decreasing
● Increasing
● No trend

Fig. 2 | Future trends using population projection from years 2020–2100. a,b,
Future trends for scenario SSP2 (middle of the road−intermediate challenges)
(**a**) and scenario SSP4 (a road divided−adaptation challenges dominate) (**b**).
Here, 'increasing' refers to cities where the population shows a monotonic
upward trend, and 'decreasing' refers to cities where the population shows a
monotonic downward trend. 'No trend' refers to cities with no discernible trend
in the population data. In **a**, many large cities are likely to experience an increase
in population over time, but this phenomenon is not as strong in **b**. In numerical
terms, ~50% of the cities will experience depopulation in SSP2, but this rises to
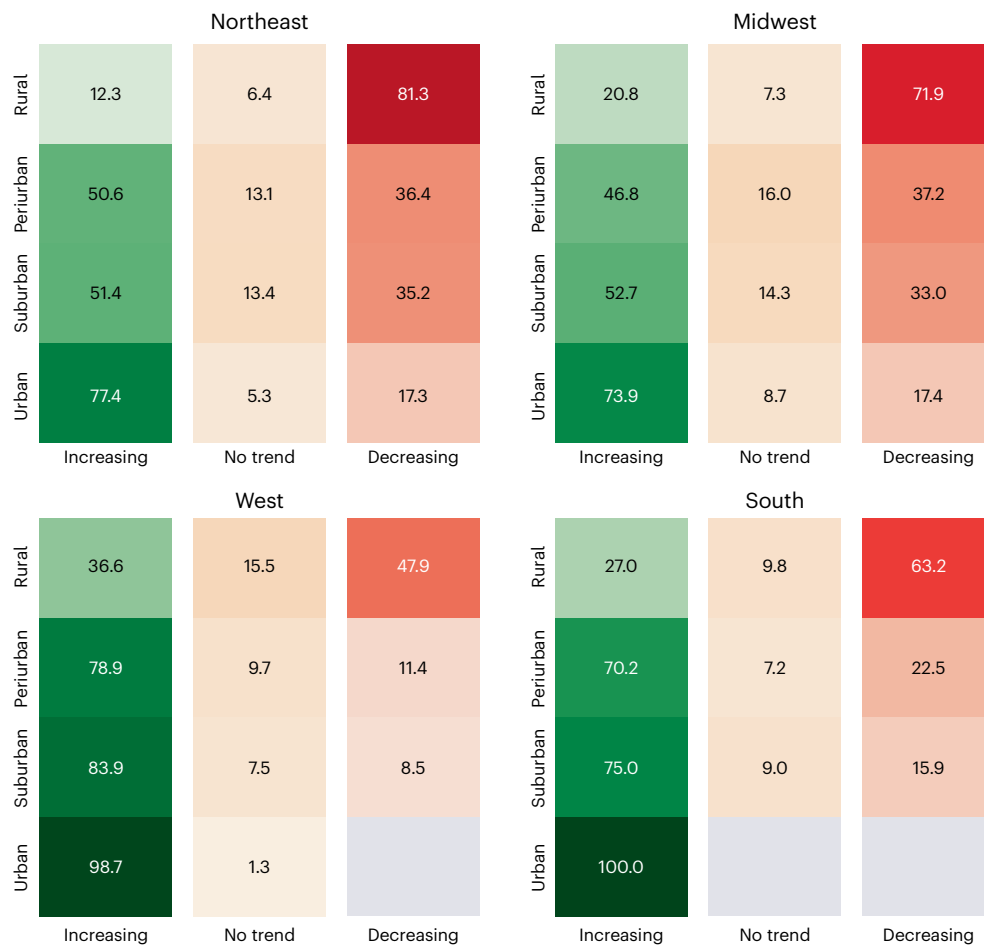~64% for SSP4.

Fig. 3 | Future population trends in SSP2 classified according to the degree of urbanization for four US regions. To simplify the comparison, the values are normalized for each city class per region. This means, in the top left figure, that of all urban cities in the Northeast region, 77.4% are likely to increase by 2100, while 17.3% are likely to depopulate. From the figure, we see that although urban cities in all regions will be gaining population, around 17% in the Northeast and Midwest are likely to depopulate. Rural places will be declining in all regions. The number of suburban and periurban cities that are likely to gain population is higher in the South and West than in the Northeast and Midwest. The grey cells with no values indicate that no urban cities are likely to lose population in the West and the South.

To leverage the insights from both datasets, we weighed them based on their error contribution in predicting the 2020 population. SSP4 was selected for estimating the weights as it exhibited the lowest weighted mean absolute percentage error when compared to the census data from 2020 (Supplementary Fig. 1). Using these weights, we derived the weighted population projection from 2020 to 2100 for all five SSPs and analyzed the population trend by applying a Mann–Kendall (MK) trend test. More information on the weight selection process is provided in the Supplementary Information.

Figure 2 shows the future population trends for SSP2 (middle of the road–intermediate challenges) and SSP4 (a road divided–adaptation challenges dominate), highlighting the variation in population trends from the two scenarios. In part, the figure reflects how current decisions may impact the future of cities, as these scenarios are defined based on socioeconomic policies in response to climate change, as defined by O'Neill and others[14]. Notably, both suggest that more than 50% of US cities are expected to lose population by 2100, compared to 43% in 2020, which is likely to generate a slew of new challenges.

In the rest of this Article we present the results of scenario SSP2, as it represents the 'middle of the road' scenario with intermediate challenges. The results for SSP1 and SSP4 are provided in the Supplementary Information. The results from SSP3 and SSP5 are not presented, because they refer to two extreme scenarios.

Next, we focus on three city characteristics—degree of urbanization, income level and vehicle ownership—and inspect their relationships with future population trends.

Variation based on degree of urbanization

For degree of urbanization, we categorize the cities into four classes—urban, suburban, periurban and rural—based on location, housing density, population and commute time. We examine the proportion of cities along with their future trends in the four US regions. Figure 3 shows the results for scenario SSP2. From the figure, we see that for all regions, urban cities are likely to increase, although 21% of the urban cities in the Midwest are likely to lose population, as Detroit (MI), Rockford (IL) and Toledo (OH) did in the twentieth century. In the West and South, a substantial share of suburban and periurban cities are likely to increase, which is likely to result in an increase in resource consumption[15,16], unless new sustainable pathways are developed.

Investigating population density, we find that cities with a higher population density are more likely to gain population (Supplementary Fig. 4). That said, the average density of depopulating cities in the Northeast and Midwest is higher than the US average, suggesting some densely populated cities may also experience a decline in population in these two regions. Interestingly, in the Midwest, the mean densities of the cities for all three trends do not vary much, while in the Northeast
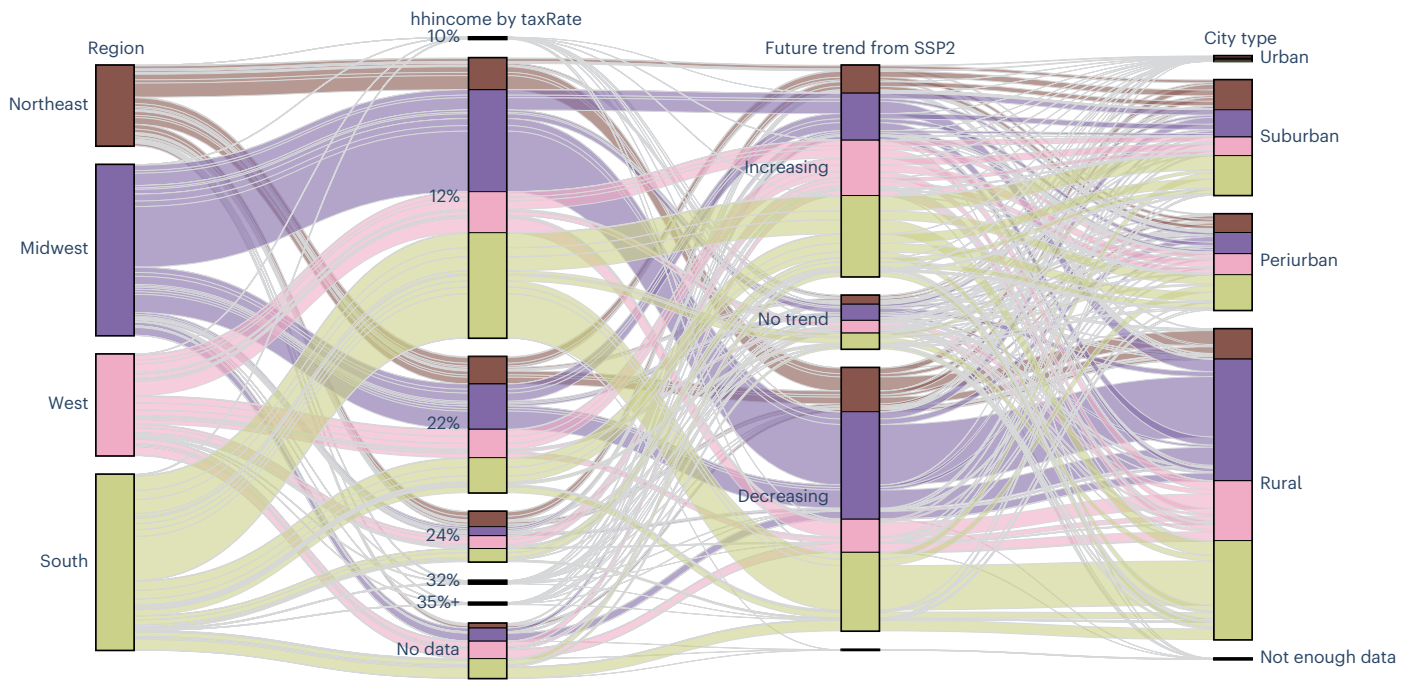
Fig. 4 | Median income in 2020 classified by tax rate with future population trends for scenario SSP2. Income data from 2020 ACS five-year median income estimates are grouped based on their tax brackets as defined by the Internal Revenue Service (IRS)[50] for filing status 'Head of the Households'. In the figure, from the cities that are likely to depopulate, many have an income tax rate of 12% or less. This phenomenon is more pronounced in the Northeast and Midwest regions. In all regions, we can also see that some rural cities with low median incomes (that is, income tax rate of 12%) are likely to gain population. NE, Northeast; MW, Midwest; S, South; W, West.

even the depopulating cities are denser than cities in other regions. These findings highlight the complex and nuanced nature of population trends in different regions and validate the need for a granular approach when planning for population dynamics. Policies to combat challenges stemming from population decline need to be localized given that each city may have unique needs.

Population trends and median income

Figure 4 shows the relationship between current income and future population trends across different regions. In the Northeast and Midwest, urban cities with lower median household income are more likely to experience depopulation over time. Such trends could exacerbate socioeconomic challenges experienced by lower-income households in these regions, given that population decline can create affordability concerns with infrastructure services, such as water and electricity, due to a dwindling tax base, and operations, management and maintenance (OMM) challenges. Across all regions, however, high-income cities in suburban, periurban and rural areas are likely to experience an increase in population, which is concerning from an environmental sustainability viewpoint if current suburban and periurban forms of planning (for example, urban sprawl) persist, as resource allocation and energy consumption tends to be higher in areas with a low population density.

Population trends and vehicle ownership

Examining the relationship between degree of urbanization, vehicle ownership and population trends, Fig. 5 shows that, in the Northeast region, urban cities with low vehicle ownership (defined as percent population with one or fewer vehicles per household) as well as some suburban and periurban cities with low vehicle ownership are likely to experience population growth. These suburban or periurban cities may be located close to urban centers, thereby having better accessibility. Similarly, in the Midwest, urban cities with both low and high vehicle

ownership (defined as percent population with two or more vehicles per household) are likely to gain population along with some suburban and periurban cities with low vehicle ownership. Urban cities showing an increasing trend in population in the South and West tend to have a higher reliance on vehicles. For all four regions, suburban, periurban and rural cities with high vehicle ownership are more likely to gain population, which can exacerbate existing accessibility challenges and further contribute to population decline in cities with limited access to transport services.

Impact of immigration

To assess the potential impact of international immigration in mitigating population decline, we examined the percent change in racial groups, particularly Hispanic/Latino and Asian communities, from the average value of the American Community Survey (ACS) 2010–2016 and 2017–2020 racial data. We further explored the relationship between the change in these racial groups in cities and the percentage of immigrant population in the MSA by plotting them (Supplementary Fig. 10). The results show a positive correlation between the percent immigrant population in an MSA and the percent change in Hispanic and Asian populations for cities in that MSA. That means that for cities where there was an average gain in population of Hispanic or Asian racial groups from 2016 to 2020, the percentage of immigrants in the respective MSA also increased. Based on this correlation, we identified cities likely to gain population from international immigration if the product of the percent gain from a racial group and the percent immigrant population in the MSA exceeds 10% of the total city population (Methods). Figure 6 depicts the cities that meet this condition. We see that cities along the periphery of metro areas have an increase in Hispanic or Asian populations. This result suggests that cities like Long Island (NY) and those around Chicago (IL), which are experiencing population loss, may still grow thanks to immigration.
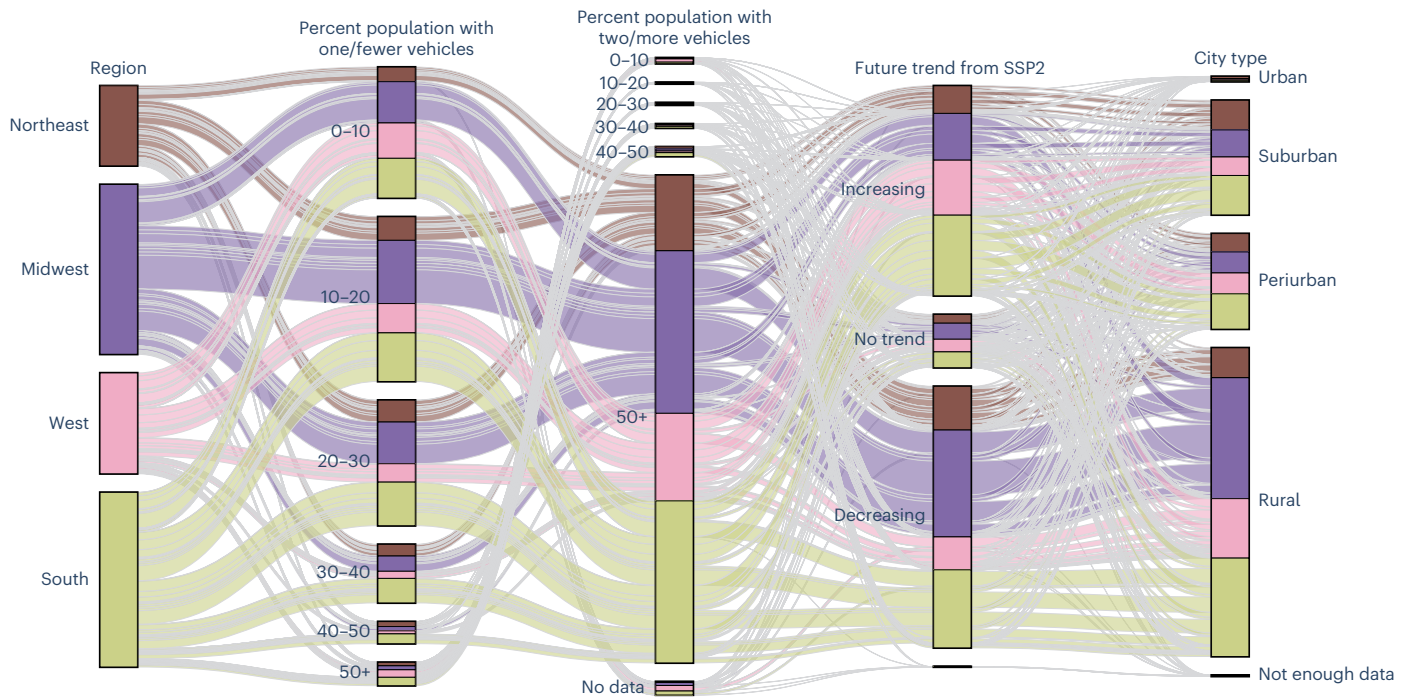
Fig. 5 | Current vehicle ownership with the future population trends for scenario SSP2. Vehicle ownership data are derived from 2020 ACS five-year estimates of the percent of the population in cities with number of vehicles available per household. The data were classified into two groups based on the number of available vehicles per household: (1) one or fewer vehicles and (2) two or more vehicles. 'One or fewer vehicles' refers to the percent of population in each city with at most one vehicle per household, while 'two or more vehicles' refers to the percent of population in each city with at least two vehicles per household. The figure shows that most cities are car-dependent. Only a few urban cities have low car dependency, which is plausible considering the low availability of transit services in US cities. Car dependency at such scales will require interventions from authorities to support aging communities in cities that are likely to depopulate by 2100. NE, Northeast; MW, Midwest; S, South; W, West.

Discussion

The findings of this Article indicate that the number of depopulating cities in the Northeast and Midwest will be higher than in the South and West regions (although many cities in the North and Midwest will still grow). In California, the southern coast may lose population, while the northern coast may gain population. Although they are growing substantially as of this writing, Texas and Utah will also see a fair share of their cities going through population loss. The projections suggest that, by 2100, all states will have cities facing some type of depopulation, except the District of Columbia and Hawaii (Supplementary Fig. 5).

Although these cities refer to places classified as boroughs, villages, towns and cities, which range from very small to large in size and population, similar challenges exist for all cities, irrespective of their size. In fact, smaller cities may experience additional challenges due to their limited financial, human and natural resources[17]. Although stagnant cities can often meet their end-user demands, depopulating cities become places with abandoned infrastructure unless conscious planning is done beforehand. Moreover, population decline does not necessarily translate to a loss in demand for basic services. For example, many city centers have lost population, but this has moved to the suburbs and requires access to services[18].

As a number of studies have highlighted already, with changes in population dynamics (for example, an increase in aging population, population decline, sociodemographic changes), infrastructure will need to be redesigned to meet the specific needs of every group[9,19,20]. Such trends are evident in Flint (MI) and Jackson (MS), for example, where population decline has led to widespread water-sector challenges[21,22]. Similarly, an investigation on transport in depopulating cities by the authors of this Article revealed that residents need pick-up and drop-off services at a low cost to facilitate the lifestyle of the often aging communities in depopulating cities[23]. Doing so may be more difficult due to financial and workforce constraints during depopulation, which only exacerbate existing infrastructure challenges[24]. In the United States, infrastructure investment already focuses more on maintenance than on capital investment[25], which, if not adjusted, can lead to certain challenges in the future. In depopulating cities, investment could be used to scale down or decommission some of the infrastructure and to rethink investment priorities. However, rightsizing without strategic planning and the evaluation of ground conditions does not always help the residents, as observed in Flint (MI)[22]. Besides, revenue losses will severely impact infrastructure OMM budgets. Given the current challenges with aging infrastructure in the United States[24], this reduced financial capacity will probably lead to a lower level of service and even cascade to create unaffordable services. For example, repaving some roads and providing some transit services may become prohibitively expensive, even if some people depend on them, and electric and water utilities may have to raise their rates given the reduced revenue from depopulation, which can create affordability issues that disproportionately impact vulnerable populations[26,27]. The challenges with telecommunication infrastructure are harder to estimate, as satellite Internet access should have become common by 2100.

If accounted for and planned properly, some of the underutilized, nonessential infrastructure could be decommissioned, and the savings might be allocated to other areas with greater needs, although decommissioning infrastructure is not straightforward (for example, water systems must continue to keep adequate pressure for fire flows and to serve users throughout the distribution system[26]). Furthermore, short-term and long-term uncertainties associated with decommissioning any infrastructure require local stakeholders' involvement to design an effective plan for decommissioning[28]. Moreover, the remaining populations are expected to have unprecedented needs (that is, the sociodemographic characteristics of the population will change). For

Legend:
— Metropolitan statistical areas
— Cities with increasing Hispanic population
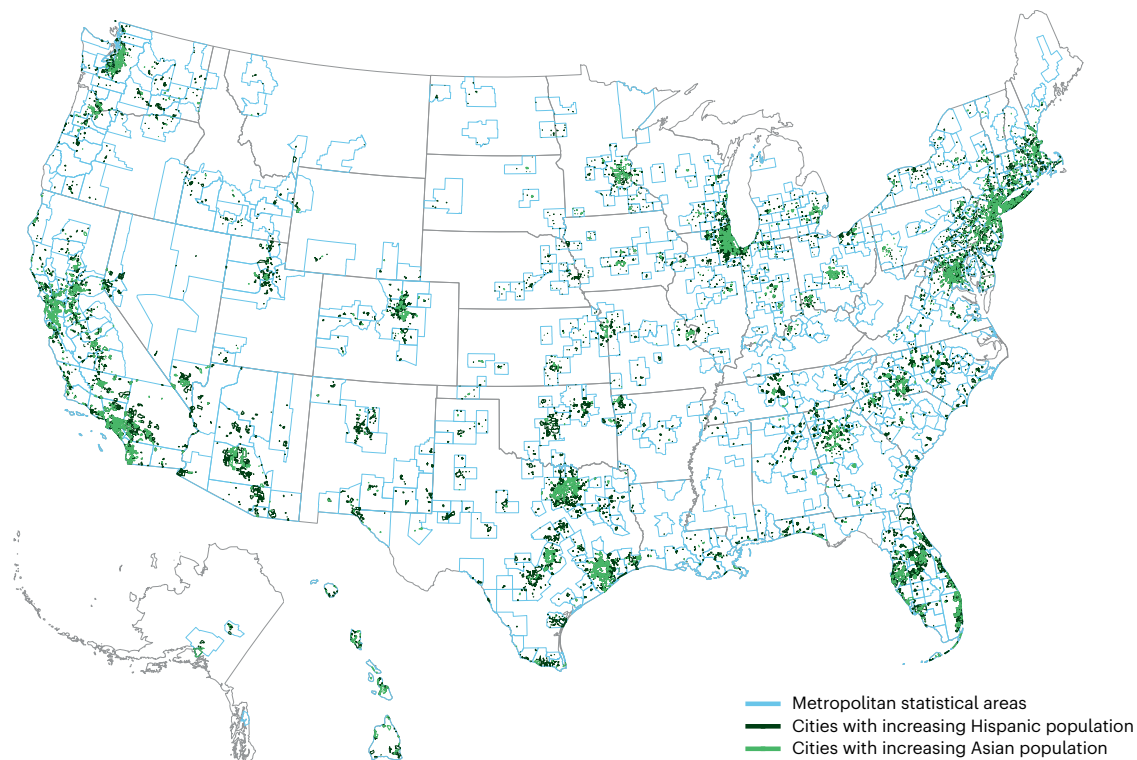— Cities with increasing Asian population

Fig. 6 | Cities with increasing international immigration (determined based on Hispanic and Asian race and on correlations from historical data) as percent of total population from current data. The figure shows that Asian and Hispanic immigrants are settling in smaller cities at the periphery of major cities. Settling close to a major city provides employment and accessibility opportunities, which can be a reason for higher immigrant settlements in these peripheral cities.

example, population decline in certain areas may lead to the closing of grocery stores, leading to food deserts. In turn, transportation systems may need to be adapted to connect vulnerable residents to the remaining grocery stores[29]. In the electricity and water sectors, these changing sociodemographic characteristics, along with the overall population change, will result in spatiotemporal demand changes, creating operational challenges[19]. Given that infrastructure systems are known to be interrelated and interdependent[30–32], it is imperative to consider how depopulation will impact all infrastructure systems. Moreover, with infrastructure deserts already existing, the challenges to meet the basic needs of residents will be amplified[33].

Conclusion

This Article studied the current population trend based on historical data and estimated future population trends from population projection for three SSP scenarios. The results revealed that about half of the 30,000 US cities are likely to lose population by 2100. As depopulation is a multifaceted phenomenon that brings with it social, economic and environmental challenges, having half of the cities depopulating is consequential. Some of the consequences faced by depopulating cities include maintaining roadways in an adequate condition, offering travel alternatives for people who cannot drive, proving clean water, maintaining enough pressure in water distribution systems, maintaining sanitary and stormwater sewers, providing electricity safely and reliably, managing solid waste properly and providing affordable housing options.

The solutions to address the challenges brought by depopulation will need to be tailored to local contexts. For example, city size has a large impact—solutions for urban cities rarely apply to rural areas. The type and size of some of the legacy infrastructure that must be maintained are important too, as are local climate and economic conditions. New practices that embrace principles of adaptability, modularity and multifunctionality should be investigated and developed. In the US context, this would also require more flexibility in administrative and financial decision-making. What is certain is that an important cultural shift in planning and engineering communities is needed, away from conventional, growth-based planning, to accommodate a dramatic demographic shift.

Limitations

To disaggregate forecasts from Hauer's projection, this Article uses the 2020 census population weighted distribution to find the projected population at the city level. Therefore, the population weights are propagated from 2020 to 2100, which results in some bias in the forecast by weighting more-populated cities in 2020 as likely to be more-populated by 2100. However, this bias is mostly limited to the cities inside a county, as county-level projections have been distributed to cities. County-level projections with Hauer's data are available for the 50 US states and the District of Columbia. Nonzero projections are available for 3,135 counties in the United States. Therefore, not all cities are included in this analysis. Cities that have altered geographic boundaries (for example, they have merged with others or developed as new cities) or that have changed both name and boundaries are excluded because of the lack of consistency in population data over time. Counties that have been incorporated after 2015 are also not included in the analysis, because projections are not available for those counties. Moreover, this Article does not explicitly consider immigration. International immigration is incorporated to some extent in the NCAR data, because the projected population has immigration assumptions as a scenario variable. However, domestic migration has not been considered in the analysis because of the uncertainty associated with it. This is an important point, as climate change is probably going to force populations to move within the United States. Yet, no systematic policies exist at the moment in the United States to manage climate-induced

domestic migration. As studied by Marandi and Main[34], climate migration impacts are not consistent for a city, nor will the impacts stay the same over time. Rather, they may present as a cyclic event, where cities go through multiple stages in terms of climate-change impacts. This goes back to the situation where every city must maintain some level of flexibility to provide livability for its residents. Furthermore, readers should keep in mind that this Article is based on current conditions and does not account for any drastic events that could impact the population (for example, major war). Rather than taking the future trend as an accurate prediction for each city, we refer to it as the 'likely future situation' for the corresponding city. This Article aims to shed light on the extent of the challenges that might result from depopulation across the United States, and it highlights the importance of revisiting mainstream planning practices that focus on growth-based planning alone. It also contributes to a growing body of research on depopulation and the need to reconfigure infrastructure in depopulating cities. The likely impacts of depopulation on infrastructure are unprecedented and require more research.

Methods
Current trend identification and labeling
Studies have defined the range of population change differently, and no universal standard exists[35–37]. To be consistent with the existing literature and to make our findings translatable, we classified cities based on the sign of percent change in population from 2000 to 2010, 2010 to 2020 and 2000 to 2020, along with their average annual change for 2010–2020. The purpose of using values of the most recent decade is their close representation of the current population data. Nonetheless, using data that are ten years apart comes with important spatial challenges (that is, geographic boundary changes). To maintain the consistency of the city boundaries over time, we inspected the census database on geographic changes and manually identified cities that have gone through 'NAME' or 'GEOID' changes. We matched and kept the most recent name used by the Census Bureau. For situations where multiple cities were merged into one, we summed their populations for the respective year(s). Similarly, for cities split into two, we applied the 2020 population ratio to find the population for 2000 and 2010 for those respective cities. Cities where the geographic changes were drastic were discarded from the analysis. More details are provided in the Supplementary Information.

To find the current population trend, we cross-tabulated the average annual change in population with the sign of change over time. The labeling thresholds were derived from the existing literature on shrinking cities, as population decline has been diagnosed as a primary indicator of urban shrinkage in both developed and developing regions[36–38]. Wiechmann et al.[36] defined cities with a continuous population decline for more than two years as shrinking cities. Oswalt and Rieniets[37] labeled cities with over 10% loss or more than 1% average loss as shrinking cities[35]. Therefore, based on these resources, we opted to label cities with an average annual change of 5% or higher as severely depopulating, from 1% to 5% as moderately depopulating, and from 0% to 1% as slowly depopulating when the signs for all three time periods were negative, and vice versa for an increasing population. Challenges appear when cities have gone through a decline in one decade and an increase in the next decade. Therefore, using the signs and percent change for the most recent time period, the cities were labeled into seven categories (presented in Supplementary Table 1), with the average annual change in population from 2010 to 2020 defined as

$$\overline{\Delta P} = \frac{1}{10}\left(\frac{P_{2020} - P_{2010}}{P_{2010}}\right) \tag{1}$$

$$\text{sign}(\Delta P_t) = \begin{cases} -1, & \text{if } \Delta P_t < 0 \\ 0, & \text{if } \Delta P_t = 0 \\ 1, & \text{if } \Delta P_t > 0 \end{cases} \tag{2}$$

$$\text{where, } \Delta P_t = \frac{P_{t_2} - P_{t_1}}{P_{t_1}}$$

$$t = \{2000 - 2010,\ 2010 - 2020,\ 2000 - 2020\}$$

Data processing for future trend forecasting
Hauer projected the population at the county level up to the year 2100 using historical census data from 1990 to 2015 (ref. 13). To forecast population trends, we first redistributed the county population to each city for all SSPs. However, some cities can expand over multiple counties. For example, New York City falls into five boroughs (county equivalents). We used the population ratio to distribute the county-level population projections to cities.

The following calculation steps were used to distribute county-level population to cities:

(1) Find the intersected area of a city within a county; for cities located in one county it is the area of the city, for cities partially located in multiple counties, it is the intersected area in the respective county:

$$A_{i_{mC}} = A_m \cap A_C \tag{3}$$

where $A_{i_{mC}}$ is the intersected area of city m that lies in county C. A_m refers to the total area of the city and A_C to the county area.

(2) Calculate the area factor as a ratio of the total city area:

$$f_{A_{mC}} = \frac{A_{i_{mC}}}{A_{l_m}} \tag{4}$$

where $f_{A_{mC}}$ is the area factor and A_{l_m} is the land area of city m.

(3) Calculate the density:

$$d_m = \frac{P_{m_{2020}}}{A_m} \tag{5}$$

(4) Find the population in the intersected area for 2020:

$$P_{A_{i_{mC}}} = f_{A_{mC}} \times d_m \times A_m \tag{6}$$

where $P_{A_{i_{mC}}}$ is the population of the intersected area and $P_{m_{2020}}$ is the Census population of the city in 2020.

(5) Calculate the population factor for the intersected area as a ratio of total county population in 2020:

$$f_{m_i} = \frac{P_{A_{i_{mC}}}}{P_{C_{2020}}} \tag{7}$$

where $P_{C_{2020}}$ is county population and f_{m_i} is the population factor for the intersected area/city.

(6) Calculate the projected population for each intersected area:

$$P_{i_{mys}} = f_{m_i} \times P_{C_{ys}} \tag{8}$$

where $P_{i_{mys}}$ and $P_{C_{ys}}$ are the projected population for the intersected area of the city and the county-level projected population from Hauer's data for county C at year y for SSP scenario s.

(7) Aggregate the intersected area population projection to find the projected population for each city:

$$P_{mys} = \sum_i^n P_{i_{mys}} \tag{9}$$

where P_{mys} is the projected population for city m at year y for SSP scenario s.

For the NCAR data, we used area weighted zonal statistics from overlapping areas of 1-km gridded projected population and city administrative boundaries to derive city-level population projections.

Once city-level projections were available from both datasets, we compared the values based on their error in predicting the 2020 city population and generated a weighted population projection for all five scenarios combining both datasets. Because we used the same weights for all five scenarios, no subscript to indicate scenario is used in the equations. The following section shows the weighting process.

Weighting the datasets

For cities that are under-projected by one set of data and over-projected by the other:

$$\Delta p_{i_k} = \left| P_{20_{i_{census}}} - P_{20_{i_k}} \right| \qquad (10)$$

$$w_{i_k} = \frac{1}{\Delta p_{i_k}} \qquad (11)$$

$$W_{i_k} = \frac{w_{i_k}}{\sum\limits_{k}^{n} w_{i_k}} \qquad (12)$$

For cities that are either under-projected or over-projected by both datasets:

$$r_{p_{i_k}} = \left| \frac{P_{20_{i_k}}}{P_{20_{i_{census}}}} \right| \qquad (13)$$

$$w_{i_k} = \frac{1}{r_{p_{i_k}}} \qquad (14)$$

$$W_{i_k} = \frac{\sum\limits_{k}^{n} w_{i_k}}{n} \qquad (15)$$

where, k = {Hauer's data, NCAR data} and $i \, \epsilon \, C$ = cities in the United States.

$$P_{w_i} = \sum\limits_{k}^{n} W_{i_k} \times P_{20_{i_k}} \qquad (16)$$

where, Δp_{i_k} is the difference in actual population and forecasted population, w_{i_k} are the weights, W_{i_k} are the weights after normalization, and $P_{20_{i_{census}}}$, $P_{20_{i_k}}$ and P_{w_i} refer to the census population in 2020, the forecasted population from dataset k and the weighted population for city i, respectively.

After computing the city-level projections, we applied MK tests to find the trend in population data. An MK test is a nonparametric test to identify whether time-series data have a monotonic increasing (or decreasing) trend or not. The null hypothesis is that the data do not possess any discernible trend. The test statistic (S) is used to label the trends. If S is a large positive number, an upward trend is indicated, whereas a large negative number indicates a downward trend. When the absolute value of S is small, no trend is indicated[39].

Estimating the impact of international immigration

Immigrants constitute a large share of the US population. According to the US Census Bureau, 13% of the US population in 2021 was foreign-born[40]. To understand the impact of international immigration, we investigated the racial change to find cities that may have been gaining more immigrants inside a metropolitan statistical area among other cities. The Migration Policy Institute provides a database containing the percent of the population that are immigrants in an MSA for the 2017–2021 period[41]. Because the immigration data refer to people staying in the MSA from 2017 to 2021, we inspected ACS five-year estimates of race and ethnicity from 2010 to 2020 for all cities. We used the percent change in different racial groups from the 2010–2016 average to the 2017–2020 average for each racial group to identify the cities that have gained more immigrants compared to the previous time period of analysis.

Although a study on the settlement of immigrants in the United States previously found that immigrants settle in the central areas of MSAs and are likely to be geographically concentrated based on country of origin and language spoken[42], more recent studies have found that high-income immigrants are more likely to settle in suburban cities with access to good public schools[43,44]. Asian immigrants living in suburban cities overrode the percent of Asians who lived in city centers[45]. Another study on the settlement pattern of Chinese immigrants in New York showed that Chinese Americans had relocated from Manhattan to outer boroughs such as Queens and Brooklyn due to the lower housing costs[46]. For Mexican immigrants, the settlement areas shifted from MSAs to nonmetropolitan, small cities where manufacturing or service economies were developing[47]. Considering the fact that 27% of immigrants in the United States are Asian and 44% are of Hispanic or Latino origin, we focused on these two main racial groups to identify cities that are likely to gain population from international immigration[40].

To find the relation between the percentage of immigrants in an MSA and the percentage change in different racial groups for cities inside that MSA, we plotted the percentage change in all racial groups along with the percentage of immigrants in their respective MSA (Supplementary Fig. 10). The plot shows that, when the percentage of immigrants in an MSA is high, their member cities show a positive change for Hispanic and Asian population from 2016 to 2020. Therefore, we assume that these cities are more likely to gain population from international immigration. However, if the Hispanic/Asian population constitute a small share of the city's total population, the increase will not be high enough to override the loss from depopulation. Therefore, we incorporated a threshold of 10% to identify cities that are more likely to gain population from immigration. The reason behind the selection of this 10% threshold is derived from ref. 37, which defined a 10% loss from total population as population decline. Therefore, if the increase in immigrant population exceeds this 10% threshold, the added population from immigration will nullify the loss. The following calculation steps were applied:

$$\Delta p_r = p_{r_{m_1}} - p_{r_{m_2}} \qquad (17)$$

$$p_i = \begin{cases} + \text{ if } \Delta p_r \times P_I > 10 \\ \pm \text{ if } \Delta p_r \times P_I \le 10 \end{cases} \qquad (18)$$

where Δp_r refers to the percent change in city population of racial group r, $p_{r_{m_1}}$ refers to the average population at time interval 1 and $p_{r_{m_2}}$ refers to the average population at time interval 2 as a percent of total city population for racial group r. p_i refers to the change in immigrant population for a city, and P_I is the percent immigrants inside an MSA. $p_{r_{m_1}}$ and $p_{r_{m_2}}$ are derived from ACS five-year estimates of race and ethnicity, and P_I can be found from the Migration Policy Institute. In equation (18), '+' refers to a gain in population that can override loss in population for that city, whereas '±' indicates there can be a gain or loss in population, but the value is not high enough to override loss in depopulating cities.

Classifying cities in an urban–rural continuum to define the degree of urbanization

We classified cities based on the degree of urbanization using four variables:

- Urbanized area as defined by the US Census
- Housing density
- Population
- Mean commute time

Specifically, we classified cities as urban if the conditions defined by the Bureau of Justice Statistics (BJS)[48] are met. To differentiate between suburban and periurban, we introduced a criterion based on mean commute time. Cities that belong to an urbanized area are classified as suburban if the mean commute time for the city is less than the mean commute time of the MSA to which the city belongs. Cities with commute times greater than the mean MSA commute time were classified as periurban. The remaining cities were classified as rural.

Joining core-based statistical area and urbanized areas

To find the allocation factor of each city in the core-based statistical area (CBSA) and urbanized areas (UAs), the Geocorr 2022: Geographic Correspondence Engine application by the Missouri Census Data Center (MCDC) was used, weighted by population[49]. CBSA provides a list of metropolitan and micropolitan areas in the United States. To find housing density in the cities, Geocorr 2022 was applied to convert census tracts to cities weighted by the number of housing units. Next, housing unit data from ACS five-year estimates for the year 2020 were used to calculate the housing unit weighted housing density for the cities.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All the data in this Article are sourced from publicly available data sources. Details on the data sources are included in the Supplementary Information. A copy of the final output dataset with future population trends for different SSP scenarios is provided in the code repository in csv format. Further details on the data can be obtained by emailing the corresponding author.

Code availability

No custom computer code or algorithm was used to generate the results. The software environments Python, R and GeoCorr 2022, the Geographic Correspondence Engine application by the Missouri Census Data Center (MCDC), were used for all data exploration and analyses based on the availability and applicability of the tools. The workflow is available at https://github.com/usutradhar/Population-Trend-Analysis.

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Author contributions

The Article was conceptualized by U.S. and S.D. The methodology and data curation were led by U.S. under the supervision of S.D. The formal analysis was conducted by U.S., L.S. and S.D. Figures were created by U.S. The first draft of the manuscript was written by U.S., and all authors contributed to edit the final draft.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

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Data collection	No custom code has been developed for this study. Open source softwares such as Python and R have been used for data analysis. GeoCorr2022 has been used for geographic conversion as mentioned in the manuscript.
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Research sample	No sample has been used. The data used covers the 50 U.S. states with Alaska and Hawaii.
Sampling strategy	No survey was carried out. Therefore, no sampling strategy is applicable to the data.
Data collection	Data has been collected from open source websites, such as: U.S. census, American Community Survey (ACS), Migration Policy Institute, NCAR data archive(Gao, J., 2017. Downscaling Global Spatial Population Projections from 1/8-degree to 1-km Grid Cells. NCAR Technical Note NCAR/TN-537+STR, DOI: 10.5065/D60Z721H), and, Open Science Foundation (Hauer, M. Population projections for U.S. counties by age, sex, and race controlled to shared socioeconomic pathway. Sci Data 6, 190005 (2019). https://doi.org/10.1038/sdata.2019.5)
Timing	The data collection is not time dependent.
Data exclusions	This study analyzes cities from the 50 U.S. states with Alaska and Hawaii. Cities outside these states are excluded in the analysis.
Non-participation	No participants were involved in the study.
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