

Article

Spatiotemporal Population Projections within the Framework of Shared Socioeconomic Pathways: A Seoul, Korea, Case Study

Youngeun Kang ¹ and Gyoungju Lee ^{2,*}

¹ Department of Landscape Architecture, Gyeongsang National University, Jinju 52725, Republic of Korea; yekang@gnu.ac.kr

² Department of Urban and Transportation Engineering, Korea National University of Transportation, Chungju 27469, Republic of Korea

* Correspondence: lgjracer@ut.ac.kr; Tel.: +82-43-841-5177

Abstract: Despite evidence of the growing importance of shared socioeconomic pathways (SSPs) in addressing climate change globally, there is a gap in research concerning the prediction of regional SSP populations. This study aims to project Seoul's population from 2020 to 2100 under various SSPs and to interpolate this population through a spatiotemporal approach. Utilizing data from the Korea National Statistical Office and international socioeconomic scenario data, we applied a regression model for predicting population growth. This was supplemented with population projections derived from cohort modeling to enhance accuracy. Population allocation within each grid was determined based on the total floor area of residential buildings. To reflect shifting population demands, we adjusted long-term population trends using observed building completion dates from 2010 to 2020. By 2100, SSP3 is projected to have Seoul's lowest population at 2,344,075, while SSP5 is expected to have the highest at 5,683,042. We conducted an analysis of grid population characteristics based on SSPs and verified the accuracy of our findings. Our results underscore the importance of refined population estimates for sustainable urban planning, indicating the potential for extending grid population estimates to other regions.

Keywords: SSP scenario; climate change response; Seoul; population downscaling; areal interpolation



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1. Introduction

Accurate predictions of climate change at a fine-grid level are crucial for effective preparation, response, and recovery, necessitating comprehensive data on climate, society, economy, and both adaptation and mitigation efforts [1–4]. Population data, including counts and densities, are indispensable for reflecting human responses to climate change. They play a pivotal role in modeling shared socioeconomic pathways (SSPs) alongside factors like urbanization, energy, education, and technology [4–7]. Such data are vital not only for climate change initiatives but also inform a range of future response studies, from economic modeling to urban planning and environmental modeling, significantly influencing resource allocation and promoting economic development and societal transformation [8–11].

Despite their importance, traditional census methods face challenges in timely and accurately capturing population dynamics [4,12]. These challenges include delays in data collection, underreporting in certain regions, and the inability to capture rapid changes due to migration or other factors. Since the 1990s, there has been a shift towards more detailed bottom-up population estimation models [13,14]. These models leverage national censuses, satellite maps, and other sources to offer improved resolution. However, they struggle with accurately projecting future populations due to potential errors in overestimation or underestimation based on current data averages [4,12–17].

In addressing these challenges, our study proposes a comprehensive strategy that integrates both population projection and spatial interpolation within the framework

of shared socioeconomic pathway (SSP) scenarios. This approach aims to enhance the accuracy of future population estimations by using projection data that reflect demographic trends, such as fertility, mortality, and migration, and high-validity auxiliary data for spatial interpolation. By combining SSP population projections with advanced spatial interpolation techniques, our research contributes to the climate change literature and provides insights for sustainable urban policies. This contribution goes beyond merely developing regional SSP scenarios to developing a comprehensive grid-based population estimation methodology, considering spatiotemporal variations to navigate the complexities of modern urban landscapes effectively.

The structure of this paper is as follows: The Introduction outlines the necessity of high-resolution population data for climate change adaptation and mitigation, the limitations of traditional census methods, and the importance of integrating SSPs in population estimates. The Literature Review examines existing population estimation techniques and their applications in various fields, highlighting the evolution of bottom-up models and dasymetric methods. The Methodology section describes the refined bottom-up estimation approach, incorporating temporal and spatial variations, and the integration of SSPs for Seoul, South Korea. The Results and Discussion section presents the high-resolution population figures for Seoul from 2020 to 2100, evaluates the reliability of estimates across SSP scenarios, and discusses implications for urban planning and climate change strategies. Finally, the Conclusion summarizes key findings, addresses the significance of the integrated approach, and suggests directions for future research.

2. Literature Review

2.1. Shared Socioeconomic Pathway (SSP) Scenarios in the Population Sector

Investigations into SSP scenarios within the population sector are centered on comprehending and probing the potential trajectories that global population dynamics may undertake, situated within the context of diverse socioeconomic circumstances [2,7,18]. SSP scenarios encapsulate narratives that delineate plausible future scenarios distinguished by distinctive socioeconomic facets, technological advancements, and environmental policies [19,20]. SSPs primarily emphasize the representation of socioeconomic factors and trajectories on population, economic growth, technological innovation, and governance. By contrast, representative concentration pathway (RCP) scenarios center on delineating pathways related to greenhouse gas concentrations and their impact on radiative forcing. Within SSP narratives, the population facet of SSPs is concerned with projecting future population size, composition, distribution, urbanization patterns, and resource management strategies [19,21]. Consequently, this sphere aims to establish connections with policies addressing both climate change mitigation and adaptation.

SSP narratives are divided into five categories: “Sustainability pathway” (SSP1), “Middle of the Road pathway” (SSP2), “Regional Rivalry pathway” (SSP3), “Inequality pathway” (SSP4), and “Fossil-fueled Development pathway” (SSP5) [22,23]. These SSP scenarios shape policies to address climate change, either individually or alongside RCP scenarios. The integrated SSP-RCP model combines various emission levels and climate change (RCP) within the framework of SSP, allowing for the exploration of a diverse set of future scenarios [19]. Previous studies have analyzed SSPs 1 to 3 and 1, 2, 3, and 5, allowing for a stark comparison of change attributes, or considered all SSP scenarios together [19,24,25]. Every pathway anticipates regional urbanization, population dynamics, and other variables, aiming to account for patterns of future development across distinct regions [26].

2.2. Advancements in High-Resolution Population Estimation Techniques

In recent years, accurately estimating population distribution has gained increasing importance across various disciplines, such as population studies, land use, environmental science, and agriculture [27–30]. This necessity has spurred the development of sophisticated interpolation or downscaling techniques, which demand the meticulous selection

of variables and systematic regional interpolation approaches. These methods are crucial for advancing sustainable urban planning, enhancing preparedness for climate change impacts, and informing policy-making with more precise regional population data [31,32].

Initially, population interpolation methodologies assigned population figures directly to target areas based on geographical extent. However, this approach was flawed, as it assumed uniform population densities across different spaces—a rarity in complex urban environments [33–35]. In response, a shift towards more nuanced statistical methods has emerged, employing a variety of data sources and analytical techniques to overcome these limitations [29,36].

The dasymetric method, an advanced area interpolation technique, represents a significant advancement in this domain. It improves data transfer control between geographical regions by leveraging auxiliary datasets such as land cover data from satellite imagery, road network information, and nocturnal lighting patterns, thus partitioning populations into finer spatial units [37,38]. More recently, attention has shifted towards leveraging detailed building-level data and population flow metrics, offering greater reliability in population estimates [7,10,35,39–41]. Utilizing metrics, including building footprints, household counts, occupancy rates, mobile population flows, and even social media data, has demonstrated the potential for unprecedented accuracy in population interpolation efforts.

There is a growing trend towards examining regional SSPs across diverse global contexts to understand the potential future trajectories of population dynamics [7,42,43]. This research highlights the limitations of broader national or international SSP estimations in capturing regional nuances [1,4]. Consequently, there is an increasing emphasis on localizing population dynamics estimates to as detailed as 30 arcs [2,7,43], necessitating the establishment of reference populations at the grid-cell level. This process primarily utilizes WorldPop data, integrating census, land cover, and topographical information to enhance estimation precision within long-term scenarios.

Despite WorldPop data's global applicability and annual updates, their predictive capacity for future population trends remains a notable limitation. This challenge has prompted researchers to explore various methodologies to enhance grid-specific population interpolation accuracy in small-scale regional units. Techniques range from gravity models calculating population changes within each grid cell to integrating urban matrices derived from representative concentration pathway scenarios, supplemented with built-up area data [4,7,43]. These approaches often revert to simplistic annual or decadal interpolation methods based on differential analysis between total population estimates and land use or land cover changes.

Addressing these methodological gaps, adopting a comprehensive strategy that integrates both population projection and interpolation within socioeconomically viable scenarios has become imperative. This holistic approach aims to refine the accuracy of future population estimations by leveraging both projection data (reflecting birth rates, death rates, and migration trends) and high-validity auxiliary data for spatial interpolation. Until now, the separate execution of projection and spatial interpolation studies has underscored the need for an integrated framework to enhance data precision effectively.

By adopting this localized downscaling strategy, the practicality of SSP scenarios for regional planning is significantly enhanced, despite the auxiliary datasets' limited geographical or temporal scope. Furthermore, expanding sophisticated dasymetric spatial interpolation techniques to include socioeconomic scenarios like SSPs, previously limited to select countries, represents a pivotal evolution. Therefore, this study seeks to merge SSP population projections with spatial interpolation, addressing climate change challenges and crafting future-oriented sustainable urban policies. The ambition extends beyond merely creating regional SSP scenarios to developing a comprehensive grid-based population estimation methodology, considering spatiotemporal variations to navigate the complexities of modern urban landscapes effectively.

3. Materials and Methods

3.1. Study Area

Seoul has the highest urbanization rate and the largest population among local governments in South Korea, accounting for about 18.6% of the national population in 2020, according to Statistics Korea. This positions Seoul as a representative microcosm of South Korea. The city's diverse population densities across its regions provide an optimal setting for in-depth analyses of population structures. The limited rural areas in Seoul further simplify the estimation process by minimizing the need to differentiate between urban and rural populations. Consequently, Seoul was selected as the focal point of this study, as it exemplifies Korean urban characteristics and underscores the pronounced centralization within the metropolitan area, more intense in Korea compared to other nations. Moreover, analyzing the population structure and trends in the capital city offers critical insights into the broader dynamics of the national population and their socioeconomic impacts.

Figure 1 illustrates the population distribution across Seoul's 25 Sigungu (regional boundaries) in 2020, using 10 equally distributed intervals in a GIS program. According to Statistics Korea, the city's population totaled 9,543,522. Songpa-gu was the most populous area with approximately 658,338 residents, whereas Jung-gu had the smallest population at 125,240. Analysis of the Sigungu reveals that 14 areas, representing 56% of the total, have a population rating of Grade 5 or lower, with an average population of roughly 381,740.9 per area. Despite Seoul's overall high population density by Korean standards, about 65% of its areas fall into this lower population size category. This discrepancy can be attributed to various factors, including the compactness of some regions and the dominance of commercial districts, while denser populations typically arise from areas with extensive apartment complexes due to residential land development projects.

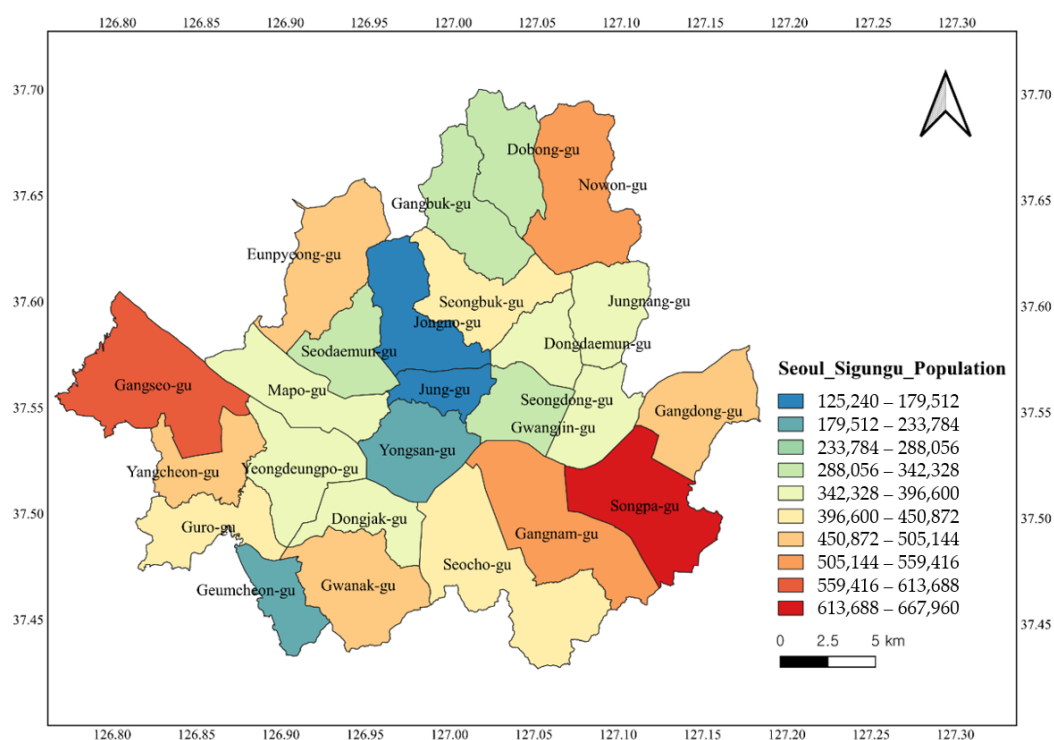


Figure 1. Seoul's population size in 2020 according to the Korea National Statistical Office.

3.2. Bridging Global and Local: From Global SSP Projections to Korea-Specific Estimates

Several international organizations, including the International Institute for Applied Systems Analysis (IIASA), produce and project a variety of SSP scenarios that incorporate population data. While these SSP data are not originally available at a regional level, they can be adapted for regional analysis.

In this study, we have adapted the Korean SSP data from IIASA, acknowledged for its precision, to reflect more recent conditions. This adaptation was necessary because the most recent IIASA data were from 2018, and our study's baseline year is 2020. We aligned our data with this later baseline by referencing population data from the Korea National Statistical Office and adjusting the IIASA Korean population SSP data using a linear regression method. This adjustment aimed to reduce errors in long-term population estimation. Specifically, we used IIASA's projected population data for Korea from 1960 to 2020 as the independent variable, with actual demographic data from the Korea National Statistical Office for the same period serving as the dependent variable. Consequently, we derived revised total Korean population estimates for SSP1 through SSP5 up to the year 2100, based on IIASA's estimations and our regression model.

The Korea National Statistical Office provides long-term population estimates at both national and provincial levels, covering all 17 provinces. Our study focuses on the long-term provincial population data for Seoul, released by the Korea Statistics Office in 2020. Our goal is to project the SSP1 to SSP5 values for Seoul by employing its population as a weighting factor, in conjunction with national-level total population estimates for each SSP scenario. This approach enables us to project Seoul's population up to the year 2100, with the baseline population set in 2020 to align with the national-level population estimate.

3.3. Population Projection Methodology at the Subregional (Sigungu) Level

Several population projection models exist, including trend extrapolation, the cohort method, the Hamilton–Perry (H-P) method, and the structural method. Each model relies on different variable relationships [10,44,45]. Among these, the cohort method is particularly prominent across various countries and organizations. It projects future populations by organizing individuals into cohorts based on their birth years and then calculating fertility rates, mortality rates, and net migration for these cohorts from a specified baseline population [46,47].

In our study, we opted for the cohort-survival model, an extension of the cohort method, for Sigungu-level population projections. This choice was made due to concerns about the potential overestimation of net migration at the Sigungu level. Notably, in the pilot phase, we encountered instances where the population of certain areas appeared to decline significantly. To address this, the cohort-survival model was applied, which simplifies the process to adding births and subtracting deaths from the base population.

$$P_t = P_{t-1} + B_{t-1} - D_{t-1} + M_{t-10 \sim 1} \quad (1)$$

In Equation (1), P_t and P_{t-1} denote the population for years t and the previous year $t - 1$. B_{t-1} and D_{t-1} represent the respective counts of births and deaths during year $t - 1$. Finally, $M_{t-10 \sim 1}$ refers to the average count of net migration spanning a 10-year period. Unlike other variables, the migration value is calculated using the average net migration from 2010 to 2019, rather than depending on the value from the previous year. This decision aims to incorporate the contemporary shifts in Seoul's demographic patterns. The reason behind this choice is the observation that Seoul's population has been increasing consistently since the 1970s. However, this trend started to reverse after 2010, primarily due to the implementation of the government's new urban strategy and the rise in real estate prices. By adopting this approach, we ensure that the analysis remains in line with the latest urban and demographic dynamics of the capital.

Subsequently, we used this model to forecast the population of Seoul's 25 Sigungu through the year 2100. We established 2020 as the base year, sourcing data on births and deaths for that year from the Korea National Statistical Office.

Considering that population estimates were previously produced for the entire city of Seoul, we refined the annual population estimates for each Sigungu based on these figures to ensure consistency with Seoul's total population. Essentially, the derived population estimates for each Sigungu served as weighting factors, allowing us to proportionally allocate Seoul's population across different years and SSPs.

3.4. Spatiotemporal Population Interpolation Methodology

Population censuses are typically conducted within administrative units by statistical agencies or bureaus, ranging in scale from census blocks to counties. These units often form a nested structure, where larger units encompass smaller ones, and the population of a larger unit is determined by aggregating the populations of its nested, smaller units. However, if these smaller units are not correctly nested, geographic overlaps can occur, causing some segments to extend beyond the boundaries of the larger units.

This study introduces a method to distribute the total population from a census unit across higher-resolution spatial units, specifically 1 km² grids. This approach to estimating population at the 1 km grid level aligns with methodologies widely utilized in previous research as a standard framework for population interpolation [4,7,14,43]. We divided the study area into 710 such grids, covering 426 administrative districts known as “dong”, indicating that, on average, approximately 1.7 grids cover one district. These districts are regularly updated with population statistics. It is important to note that grid sizes might overlap with layers containing population data, and there is no one-size-fits-all rule for determining the optimal grid size. This grid system also enables straightforward comparisons with datasets from other studies, such as WorldPop and LandScan, thus facilitating the validation of our grid-based population estimates.

However, it is essential to recognize that integrating gridded population data with census data may lead to discrepancies between the boundaries of census units and grid units, especially in areas where they overlap. These boundaries do not form a nested structure, meaning that the population of a larger unit cannot simply be calculated by adding together the populations of smaller units within it. Areal interpolation is the method used to estimate populations across different layers when their boundaries do not align geographically [48]. This process involves designating one layer as the target layer, where populations are estimated, and another as the source layer, which provides the necessary population information for those estimates [48,49]. In our study, the grid units serve as the target layer, and the census units act as the source layer. We employ the areal interpolation method to distribute the total population from each census unit across the corresponding higher-resolution grid units.

Population data are typically collected across different levels of census operations. To achieve the desired spatial resolution, population area interpolation is frequently required [7]. In the field of areal interpolation research, a range of techniques are applied to estimate populations in a target layer using information from a source layer [50]. One fundamental technique, the areal weighting method, estimates the population in the target layer by considering the area overlap with the source layer [48,51]. This method distributes the population to the target layer based on the proportion of overlap, although it simplistically assumes a uniform distribution of population across both layers, which may not reflect reality.

Dasymetric interpolation methods refine population estimation accuracy by integrating auxiliary data [52,53]. An example is the binary dasymetric method, which focuses solely on habitable areas for more precise population estimation, excluding non-inhabitable spaces like water bodies and uninhabited land [54]. This approach increases estimation precision by categorizing ancillary information into binary classes (habitable/uninhabitable) and further into poly-categories (high/medium/low density) for detailed analysis [54,55].

The enhancement of areal interpolation methodologies relies on the utility of auxiliary data to better differentiate relevant information from extraneous noise, thus improving the accuracy of the interpolation process. Various studies have explored using additional information to increase the precision of population estimates [17,41,56]. Satellite imagery, offering detailed land cover information, night-time population distribution, and other environmental variables, presents a valuable resource for population estimation, available globally in a standardized grid format. For instance, global population databases like WorldPop have emerged from the regular compilation and release of satellite imagery and demographic data on a worldwide scale. Furthermore, Huang et al. [39] introduced a

methodology to enhance grid-level population estimation accuracy by employing computer-generated building footprints from Microsoft’s Bing Maps as additional information. This approach was empirically shown to be an improvement over traditional methods by using statistical analysis to evaluate the accuracy of population estimation techniques.

As indicated in the results, employing total floor area as supplementary information for estimating population significantly surpasses other traditional methods, such as areal weighting and both binary and poly-categorical dasymetric methods, in terms of precision. Consequently, our findings contribute methodologically. While high-resolution grid population data, such as WorldPop and LandScan, are valuable in areas without practical alternatives, there remains significant merit in methodological improvements aimed at enhancing the accuracy of population estimates through the use of auxiliary information that is not derived from global-scale satellite imagery. In this vein, our research sought to exploit the methodological advantages of the dasymetric approach by integrating more sophisticated ancillary data for the most precise population estimates achievable. The primary ancillary data utilized in this study is the total floor area of individual buildings (refer to Figure 2 for an illustrative overview).

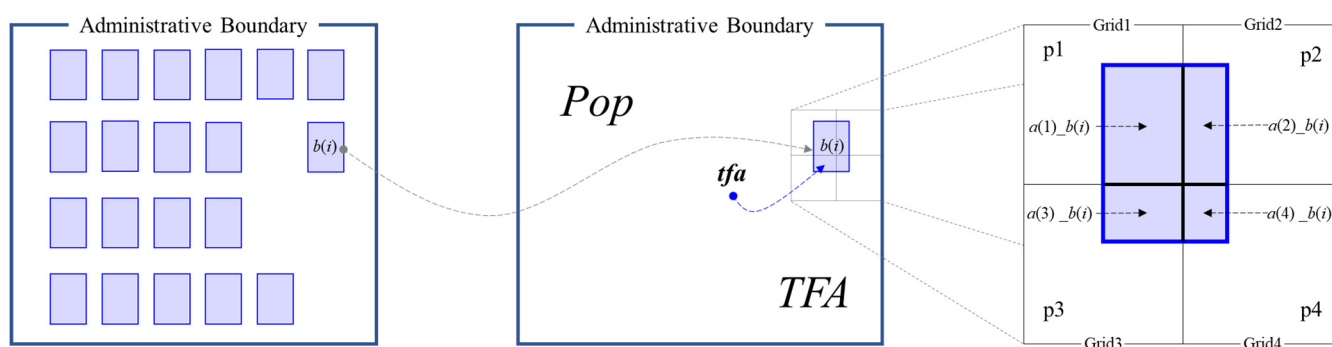


Figure 2. Conceptual design of the dasymetric method using building data.

In Figure 2, the term “administrative boundary” refers to the census unit containing population information. Within this boundary, there are 20 residential buildings denoted as $b(i)$ with the same total floor area denoted as tfa , each represented as a blue rectangle. For instance, if the floor area of a ten-story building is designated as f , tfa of the building is determined by multiplying f by 10. For explanatory convenience, all buildings in Figure 2 were assumed to have the same number of stories. In reality, each building varies in its number of stories, and the height of each building is taken into consideration when estimating the population.

TFA represents the sum of the total floor areas across all 20 buildings. The figure illustrates a building divided into four parts by square grids ($tfa = a(1)_b(i) + a(2)_b(i) + a(3)_b(i) + a(4)_b(i)$). The total population within the administrative boundary, denoted as *Pop*, is distributed among the buildings in proportion to their total floor areas. Each building receives an allocation of $Pop/20$ population because tfa is constant for all buildings. $a(1)_b(i)$ corresponds to the area of one of the four divided building segments, and the population in *Grid1*, $p1$, is assumed to be proportional to $a(1)_b(i)$. Thus, it is calculated as $\frac{Pop}{20} \times \frac{a(1)_b(i)}{tfa}$ in Figure 2. The populations in other grids ($p2$, $p3$, and $p4$) are estimated using the same approach.

The building code in Korea classifies structures into 29 distinct types according to their intended use. Among these classifications, single-family houses and apartment buildings are explicitly designated for residential purposes. The Korean Ministry of Land, Infrastructure, and Transport (MOLIT) offers spatial data, termed “building information by use”, which include details on both the floor area and function of buildings. In our study, we utilized this spatial data to estimate the residential population.

Equation (2) outlines how to estimate $p(i)$, the population allocated into $Grid(i)$, where segments of r buildings are completely contained within.

$$p(i) = \sum_{j=1}^r \frac{a(i)_b(j)}{tfa(j)} \times pop_b(j) \quad (2)$$

$pop_b(j)$ represents the population assigned to building j . A portion of $pop_b(j)$ contributes to the estimated population in $Grid(i)$ based on the proportion of the segmented area $a(i)_b(j)$ to $tfa(j)$. The sum of these segmented populations determines the estimated population in $Grid(i)$.

For all grids, we estimated populations on a yearly basis over the past decade to conduct population projections. The projected population in grid i in t is denoted in Equation (3).

$$p_t(i) = p_{t-1}(i) \times \left\{ \frac{w1 \times (1 + \beta(i)) + w2 \times \gamma(i)}{w1 + w2} \right\} \quad (3)$$

$p_{t-1}(i)$ indicates the projected population for the previous year, $t - 1$, and the expression within the parentheses in Equation (3) signifies the population growth/decline rate. $\beta(i)$ represents the annual population growth/decline rate in the projection for grid i . Population growth/decline rates for each grid were determined as regression coefficients in the population estimation process, using estimated annual populations from the past 10 years in $Grid(i)$. If $\beta(i)$ is, for instance, 0.01, the population is expected to increase by 1% from the previous time $t - 1$ after one year. $\gamma(i)$ aims to explain short-term and erratic circumstances that are considered to have been observed in the process of deriving $\beta(i)$. In this study, $\gamma(i)$ is calculated as the ratio of $p_t(i)$ to $p_{t-1}(i)$ for randomly selected t . While $\beta(i)$ represents the long-term trend of population growth/decline in the future, $\gamma(i)$ reflects the short-term, unpredictable changes in the population projection process. $w1$ and $w2$ denote the parameters of weighing the importance of the long-term trend and the short-term fluctuation in the population projection. For the empirical estimation of the population, the values of the parameters are both set to one. Although the choice of parameter value is arbitrary and the relative importance of long-term versus short-term changes must be empirically calibrated using auxiliary data, undertaking an additional estimation process to ascertain the parameter values is overly demanding within the constraints of this paper. In this context, we contend that equating the parameter values is a viable option. One noteworthy point is that upper bound in the projected population needs to be imposed to $Grid(i)$, since it has a limited geographical area. The maximum limit is determinable by dividing the total floor area of buildings in $Grid(i)$ by per capita area, representing the minimum required residential space per person, a figure subject to municipal regulations. Another noteworthy fact is that the minimum projected population value is zero. This can be attributed to the possibility that, for some reason, the expression within the parentheses in Equation (3) may turn negative, leading to a projected population less than zero, which is logically inconsistent.

Figure 2 illustrates the high-resolution population projection/estimation process, aligned with the spatiotemporal approach and incorporating the SSP scenario extension. The process is bifurcated into two methodologies: a top-down approach that integrates multiple variables as determined by experts and a bottom-up technique implemented within specific areas using a population projection model, such as the cohort model. Our study distinguishes itself from existing research through its hybrid approach, combining global data and information derived from the top-down method with a bottom-up technique involving cohort modeling to project population figures at the grid level.

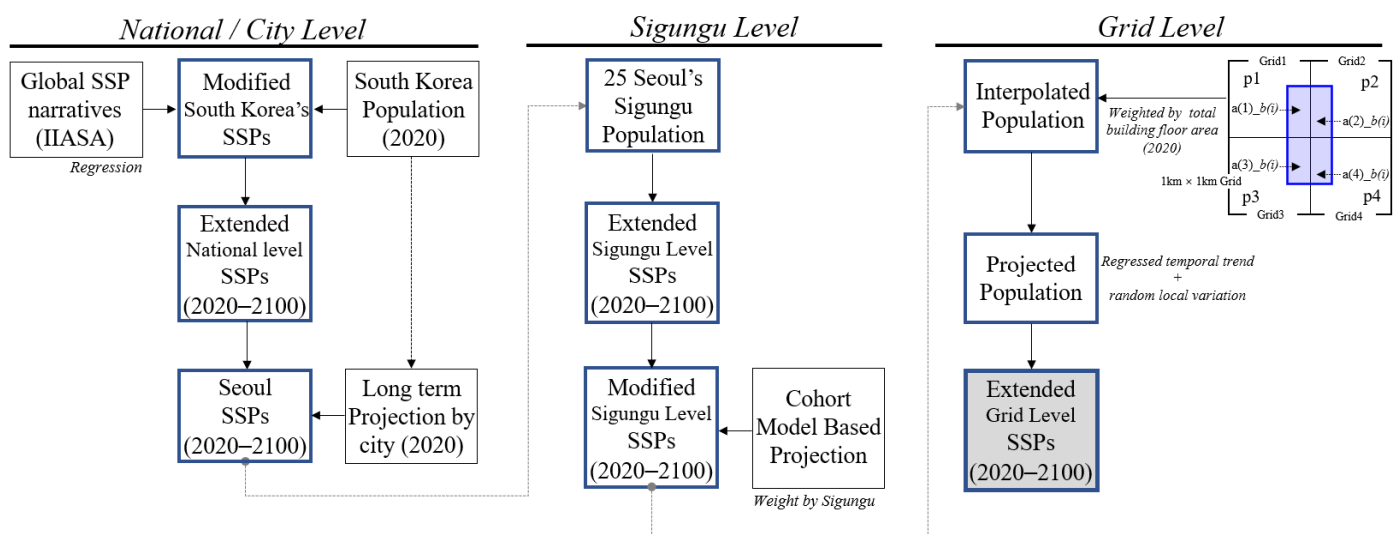
To enhance the accuracy of population projection/estimation, we analyzed spatial areas across various scales, ranging from national and provincial to Sigungu and, ultimately, grid levels. Data sources encompass population and building information from the Korea National Statistical Office, as well as regional boundary data, detailed in Table 1. The final results were visualized using QGIS and Python programming.

Table 1. Study framework and data used.

Division	Description	Data Used
Baseline	Population trend	Set 2020 as the baseline and conduct estimates in five-year increments through to 2100 Korean Statistical Information Service (https://kosis.kr/index/index.do , accessed on 5 May 2023)
	Gridded population trend	Set 2010 as the baseline and perform annual estimates up to 2020 (residential building completion date by year) GIS building integrated information (https://www.vworld.kr/dtmk/dtmk_ntads_s002.do?svcCde=NA&dsId=5 , accessed on 5 May 2023)
Spatial Boundary	Seoul-si (25 Sigungu)	National Geographic Information Institute (https://www.vworld.kr/dtmk/dtmk_ntads_s002.do?searchKeyword=%EC%8B%9C%EA%B5%B0%EA%B5%A&searchOrganization=&searchBrmCode=&searchTagList=&searchFrm=&pageIndex=1&gidmCd=&gidsCd=&sortType=00&svcCde=MK&dsId=30604&listPageIndex=1 , accessed on 5 May 2023)
SSPs	South Korea's SSP1, SSP2, SSP3, SSP4, and SSP5	SSP database of the International Institute for Applied System Analysis (2018)
Population Projection/Estimation	National level	Revision and expansion of Korea's population size based on global SSPs (IIASA) SSP database of the International Institute for Applied System Analysis (2018) Korean Statistical Information Service (https://kosis.kr/index/index.do , accessed on 5 May 2023)
	Sigungu level	Revise the cohort model using population, birth rate, and death rate Korean Statistical Information Service (https://kosis.kr/index/index.do , accessed on 5 May 2023)
	Grid level	Allocation by grid (30 arc sec) through residential building total floor area National Geographic Information Institute (https://map.ngii.go.kr/ms/map/NlipMap.do?tabGb=statsMap , accessed on 5 May 2023) GIS building integrated information (https://www.vworld.kr/dtmk/dtmk_ntads_s002.do?svcCde=NA&dsId=5 , accessed on 5 May 2023)

Note: Sigungu is the name of an administrative boundary that divides subregions in Korea.

Figure 3 provides a summary of the overall study structure. Beginning with Seoul's population estimation using SSP scenarios, which incorporates international and domestic trends, population estimation and interpolation were systematically conducted at Sigungu and grid levels.

**Figure 3.** Study framework and process.

3.5. Assessing the Precision of Population Projections

Due to the unavailability of actual outcome data for future population estimates, it is not feasible to assess the accuracy of the estimated population interpolation results in this study. Therefore, we focused on evaluating the reliability of the population interpolation results utilized as the 2020 baseline data.

The process for gauging population interpolation accuracy involves the initial creation of population estimates on a 1 km grid basis. Subsequently, a sub-boundary layer referred to as “dong”, fully nested within the Sigungu district layer, is overlaid on the grid layer. This procedure generates multiple polygon segments, each containing information about the estimated population. The cumulative population within a specific “dong” segment is then compared with the actual population obtained through a statistical survey (Korean Statistical Information Service) of that “dong”.

To quantify accuracy, the Root Mean Square Error (RMSE) metric was employed. RMSE assists in identifying the extent to which the population interpolation results, based on the total building area used in this study, deviate from the results provided by Statistics Korea. Consequently, the RMSE metric was utilized to assess the accuracy of area interpolation using total floor area by contrasting it with the RMSE values of area-weighted and building footprint area methods.

4. Results

4.1. Projecting Seoul's Population Dynamics: An Estimation from 2020 to 2100

Figure 4 depicts data extracted specifically for Seoul from the Korean national-level SSP scenarios, indicating a substantial decline in Seoul's population from 9,426,791 in 2020, as projected by SSP2, to 3,954,577 by 2100. While the variation in population among SSPs in 2020 was relatively modest, the disparity in population projections for 2100 is pronounced. Notably, SSP3's population estimate for 2100 is anticipated to be 2,344,075, marking a decrease of approximately 74% from 2020. The population rankings by SSP in 2020 are consistent with those in 2100, with SSP5 expected to have the highest population and SSP3 the lowest, reflecting trends seen in population estimates for other developed countries (Table 2).

The minor population increase observed in some SSP scenarios from 2050 to 2055 can be attributed to the anticipated peak in the overall national population during this period, despite a general decline in population growth.

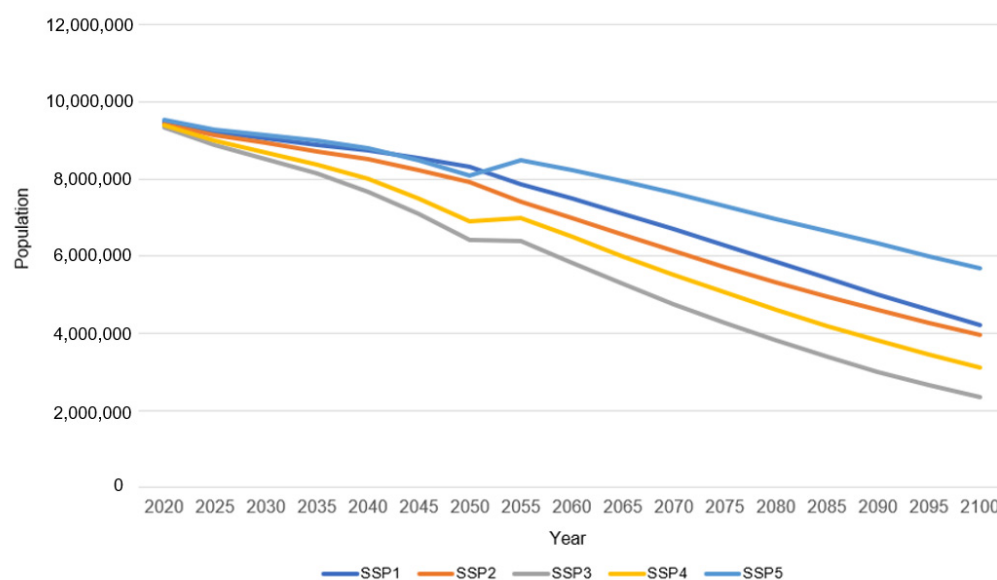
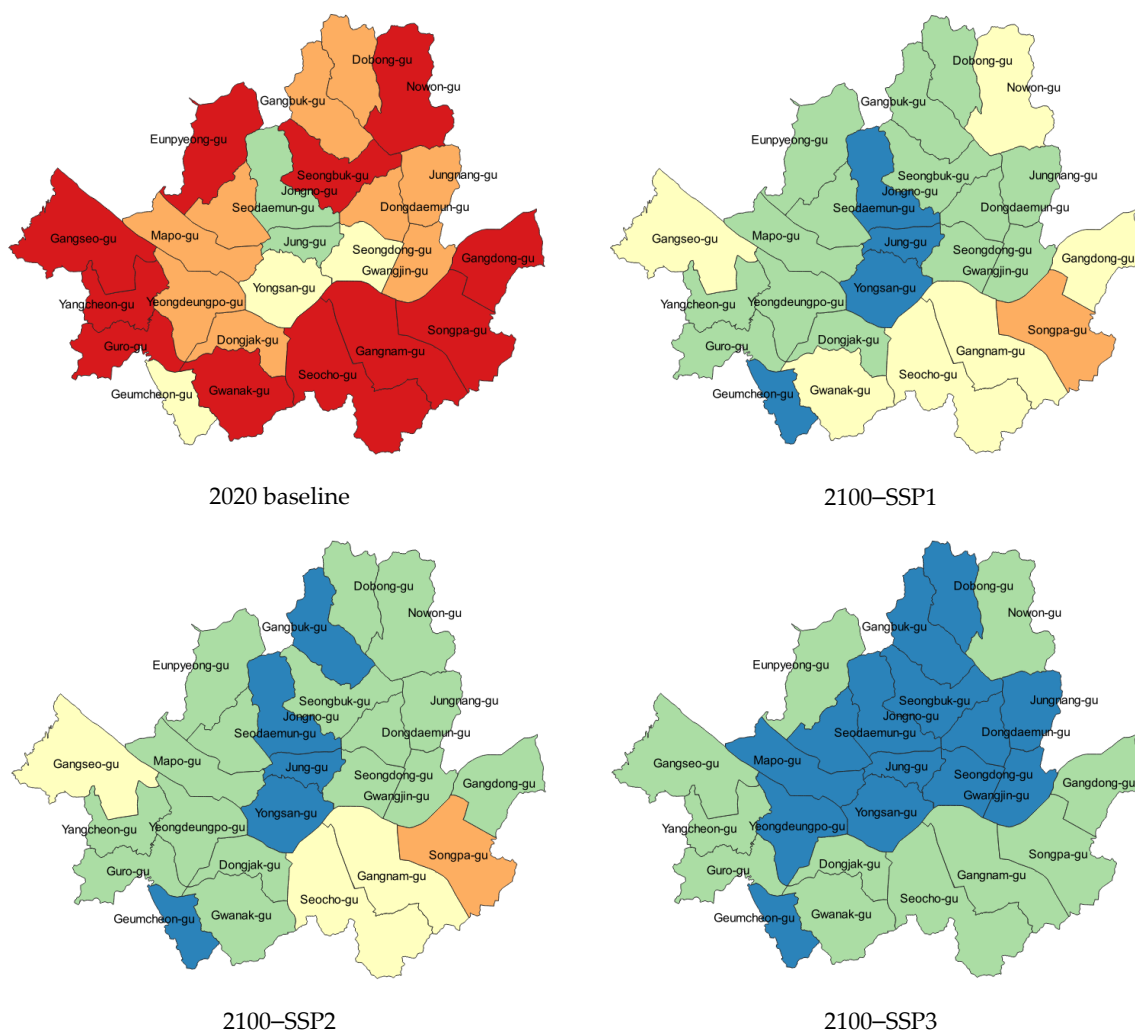


Figure 4. Population estimates for Seoul at five-year intervals by 2100.

Table 2. Population estimates for the years 2020, 2050, and 2100.

SSP	2020	2050	2100
SSP1	9,468,594	8,312,896	4,217,598
SSP2	9,426,781	7,927,544	3,954,577
SSP3	9,334,082	6,426,733	2,344,075
SSP4	9,378,657	6,905,625	3,095,485
SSP5	9,530,722	8,079,551	5,683,042

Figure 5 displays the distribution of Seoul's 25 Sigungu, segmented into 10 equal intervals based on the 2100 SSP1–5 scenarios, highlighting an evident trend of population decline from 2020. Notably, the areas with the highest and lowest populations in 2100 reflect the initial population distribution of 2020. Specifically, Songpa-gu maintains the highest population among all regions, with numbers ranging between 192,178 and 465,921 at the Sigungu boundary, while Jung-gu records the lowest, approximately 50,000. Other regions anticipated to have relatively high populations, apart from Songpa-gu, are Gangseo-gu and Gangnam-gu. Regions to the north of Seoul, such as Nowon-gu, Dobong-gu, and Gangbuk-gu, are significant for their above-average population distribution in 2020, which shifts towards a lower population distribution by 2100. This change is primarily attributed to an increase in the elderly population and a decrease in birth rates in these areas, affecting the long-term population distribution estimation.

**Figure 5.** Cont.

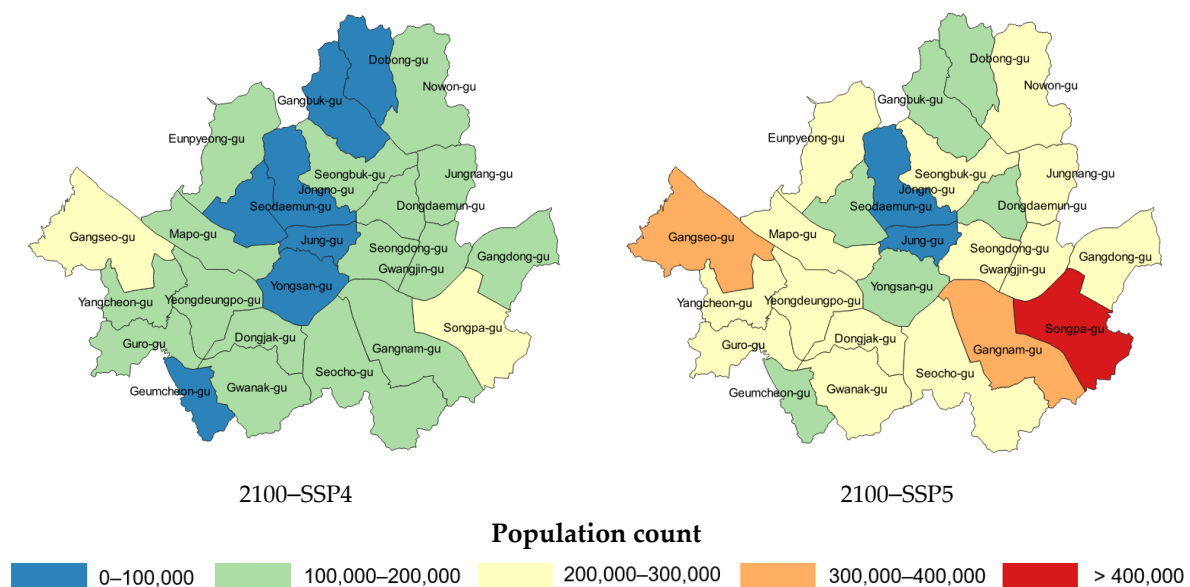


Figure 5. Estimated SSP1–5 population at the Sigungu level as of 2100 compared to 2020.

4.2. High-Resolution Population Allocation

4.2.1. Regional Variations in Population Distribution

Initially, the accuracy of population estimates for each grid was verified through a comparative analysis using the Root Mean Square Error (RMSE) metric, yielding the following results: the RMSE for the areal weighting method was 17,952, while the building footprint method yielded an RMSE of 7962. The total-floor-area-based method resulted in an RMSE of approximately 4519, indicating superior performance compared to the other two methods.

Figure 6 depicts variations in population distribution across different SSP scenarios in 2100, based on the 2020 grid population distribution. In 2020, the population was categorized into five grades: 0 to 5000 (Grade 1), 5000 to 15,000 (Grade 2), 15,000 to 25,000 (Grade 3), 25,000 to 35,000 (Grade 4), and above 35,000 (Grade 5, representing the highest population).

Overall, the 2100 population, under all SSP scenarios, shows a decline compared to 2020. The 2020 population distribution was fairly even, except in some peripheral areas. By 2100, the predictions indicate an increase in grids with minimal or no population, especially towards the outskirts. In 2020, the majority of the population fell within Grade 3 (15,000 to 25,000 per grid), but by 2100, there is a significant reduction in Grade 3 grids, suggesting a trend towards regional population polarization.

SSP1, viewed as the most favorable scenario, shows a higher total population than SSP2 but similar population grade distributions. Analyses of SSP3 and SSP4 reveal a lack of Grade 5 outcomes, the category with the highest population, and an increase in grids with very small or no populations. Additionally, an examination of population changes by Sigungu indicates the disappearance of some highly populated grids north of Seoul by 2100.

Table 3 outlines the gridded populations for each SSP in 2020 and 2100. Within the scope of SSP2, the average population per grid in 2020 was 13,277 individuals, with the highest population density in a grid reaching 67,127 people. Discounting grids devoid of population distribution, the minimum population recorded in 2020 was one person.

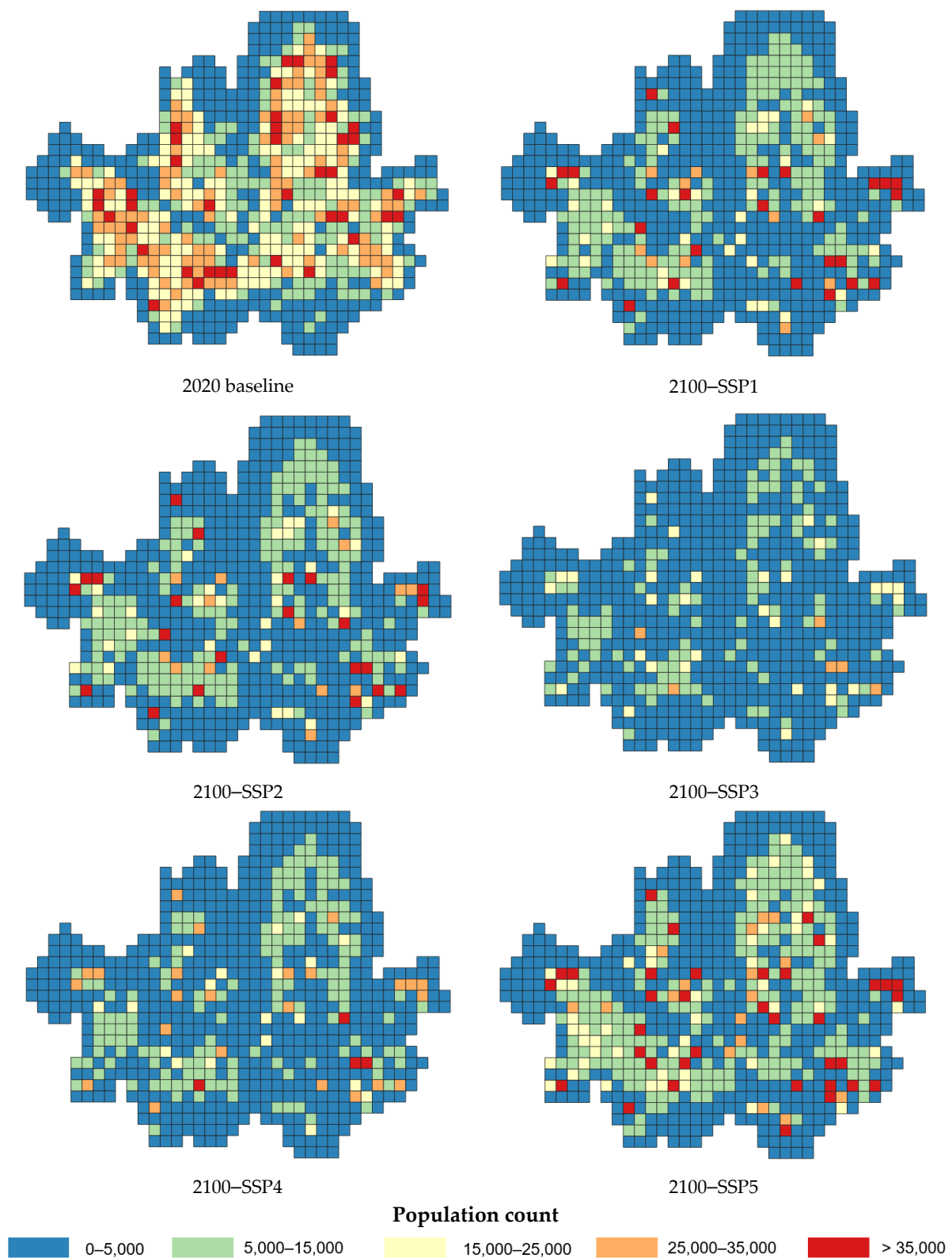


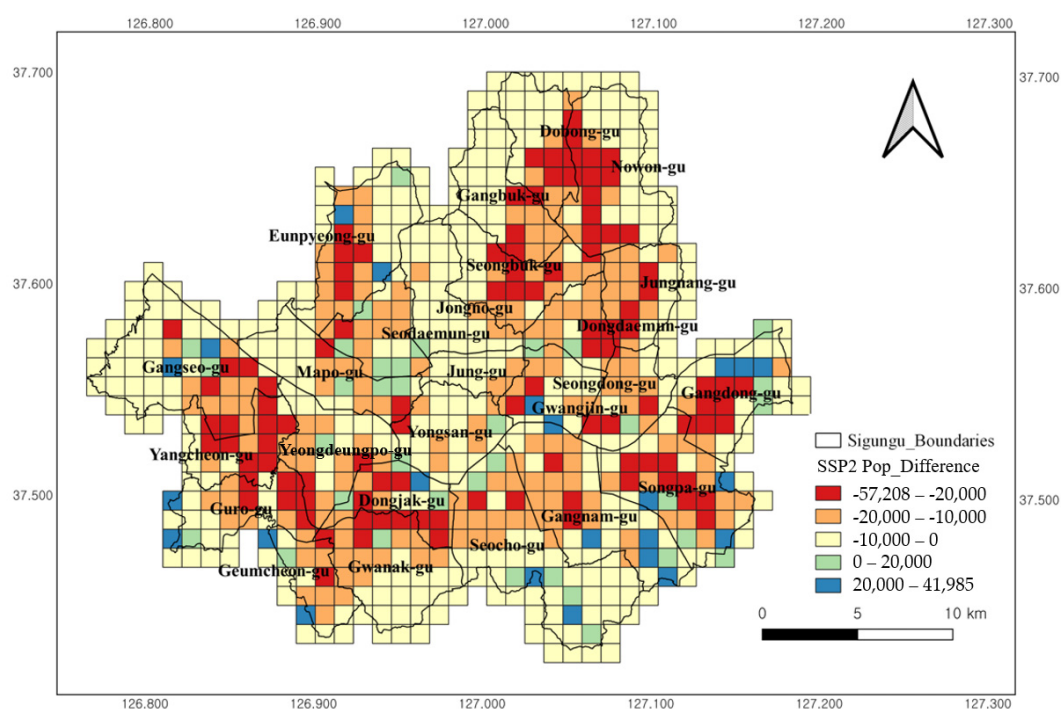
Figure 6. Population estimation by SSP in 2100 based on gridded population in 2020.

Table 3. Comparison of population differences between grids by SSP, 2020–2100.

Division	Mean	Max.	Min.	Std.	Max. Difference by Grid with 2100
2020 SSP1	13,336	67,425	1	12,726	50,734
2020 SSP2	13,277	67,127	1	12,670	51,567
2020 SSP3	13,147	66,467	1	12,545	57,859
2020 SSP4	13,209	66,784	1	12,605	54,932
2020 SSP5	13,424	67,867	1	12,810	44,846
2100 SSP1	5940	60,474	1	9452	-
2100 SSP2	5570	56,703	1	8862	-
2100 SSP3	3302	33,611	1	5253	-
2100 SSP4	4360	44,385	1	6937	-
2100 SSP5	8004	81,487	1	12,736	-

Significantly, by 2100, there is a notable decrease in population, with grid populations for both SSPs reducing by more than half relative to the 2020 data. For SSP2 specifically, the average population per grid in 2100 diminishes to 5570 individuals, with the peak population within a grid being 56,703 people. Despite minimal disparities in grid populations within the SSP scenario in 2020, marked differences in grid population densities become apparent by 2100. Specifically, the highest grid population for each SSP in 2100 varies from 33,611 (SSP3) to 81,487 (SSP5), indicating that while the overall population size was greater in 2020, certain grids in 2100 may exhibit higher population densities than those observed in 2020.

Figure 7 illustrates population variances across grid areas based on long-term projections, contrasting the population distribution in 2020 by SSP with that in 2100 under the same SSP. SSP3 shows the most significant difference in population figures between 2100 and 2020, with a variance of 57,859 individuals, as detailed in Table 3. Similar patterns of population variation are noted across other SSPs as well.

**Figure 7.** Difference between SSP2 gridded population in 2100 and 2020. Note: As SSP2 assumes the continuation of current trends among the five scenarios, its results were utilized for their representativeness.

Notably, the significant disparities in population between 2100 and 2020 are not localized to specific areas but are dispersed across various locations. This distribution may be due to these regions initially having higher populations than other grid areas, resulting in notable population fluctuations over time. Despite a general trend of population decline in 2100 compared to 2020, certain grids in 2100 exhibit populations that exceed those recorded in 2020. Areas such as Songpa-gu, Gangnam-gu, Gangdong-gu, Seongdong-gu, and Eunpyeong-gu are highlighted for their particularly widespread grids. This pattern can be attributed to these locations having relatively high birth rates, net migration rates, and a significant increase in new construction compared to earlier periods.

4.2.2. Temporal Changes and SSP Scenario Comparisons

In our analysis of population estimates from 2020 to 2100, we examined variations based on time periods and SSPs, in addition to differences related to spatial grids. Initially, Figure 8 presents the trends in the overall average and standard deviation of gridded populations at five-year intervals. The results show a consistent decline in population numbers, with a minor slowdown in the rate of decrease around 2055, followed by a continuation of the downward trend. Throughout this long-term trajectory, the gap in standard deviation narrows, mirroring the reduction in average population per grid.

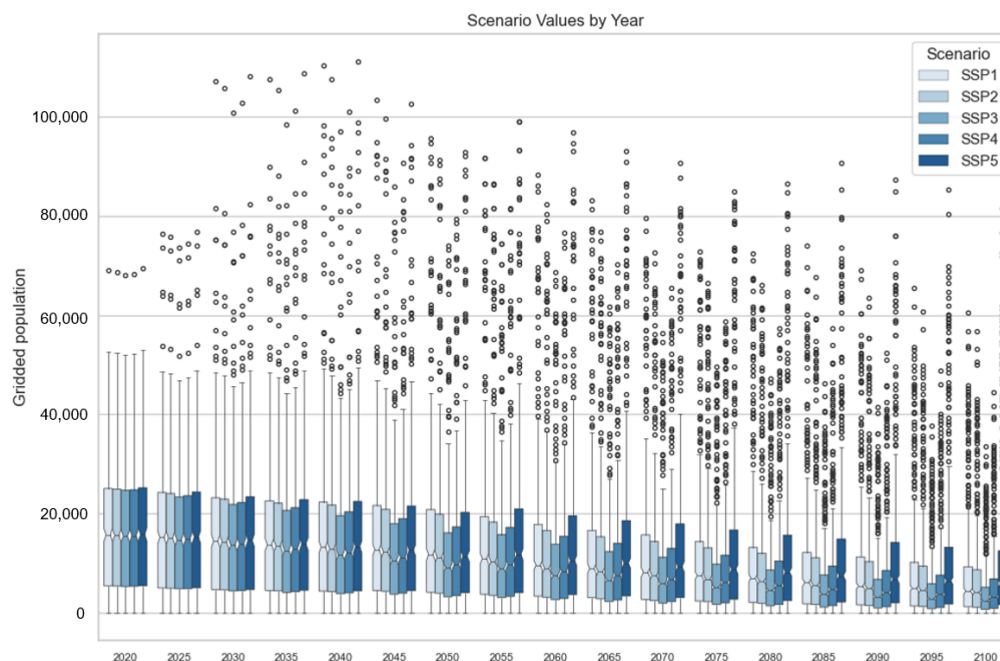


Figure 8. Variations in population by period and SSP over five-year intervals.

Additionally, Figure 8 showcases the results of comparing population sizes and deviations within each allocated grid for the 2100 SSPs. Generally, scenarios with a higher average population per grid demonstrate greater variation. SSP1 and SSP2 show similar population sizes and standard deviations, whereas SSP3 features the smallest grid-specific population sizes and deviations. Conversely, SSP5 presents the largest average grid population size and the most considerable variation, indicating that with an increase in total population size, significant disparities in population sizes between individual grids can be observed.

5. Discussion

5.1. Leveraging SSP-Based Projections for Urban Sustainability

Solely depending on traditional urban planning methods falls short of addressing the challenges posed by dynamic changes, complex environmental factors, and uncertain territorial expansion [57]. Climate change, a critical concern, must be integrated into

sustainable urban planning efforts [58,59]. In response to climate change risks, many researchers have developed urban planning technologies and policies that include both physical and programmatic elements, focusing on “adaptation” [60,61]. Examples of such measures include promoting relocation from coastal areas, implementing green curtains, cool share facilities, afforestation efforts, employing building pilotis, and managing areas vulnerable to climate change. While these measures are effective short-term strategies for climate change preparedness, they may not sufficiently address long-term climate challenges due to potential oversight of future policy impacts.

Embracing SSPs for scenario prediction and policy formulation within climate pathway studies can mitigate these limitations [6,21,62]. SSP scenarios are vital for sustainable urban planning, offering a framework to explore future urban challenges and opportunities. Wan et al. [7] demonstrated that high-resolution population downscaling based on SSPs informs policymakers’ decisions on disaster prevention, resource allocation, infrastructure development, and regional services provision. Previous research emphasizes the importance of aligning policy decisions with these projections [24,63].

This study highlights the significance of effective “urban resource allocation”. Projected population and distribution data are essential for tailoring urban infrastructure provision in each region, providing insights into future population concentrations or declines. Demographic data play a crucial role in advancing sustainability goals and assessing human impact on the planet [32]. Furthermore, population estimates are key to future urban planning and disaster management [64,65]. For example, when assessing regional sustainability, these projections can be directly utilized to differentiate between regions with vulnerable populations and those with high population density, guiding decisions on where to invest in or restrict infrastructure development. Additionally, they can play a crucial role in mapping population movements and creating risk maps by identifying areas prone to climate change impacts in advance, through the integration of climate prediction models and urbanization rates.

However, many local governments in Korea risk overinterpreting medium-to-long-term population projections to attract urban development. While such forecasts may stimulate short-term development and local revitalization, they risk resource wastage if not matched with an appropriately sized population. Such misallocation hinders climate change mitigation efforts, as excessive development can lead to substantial resource waste and increased carbon emissions.

Furthermore, the SSP5 scenario, which anticipates large-scale carbon-based development, underscores the risk of excessive polarization regardless of overall population growth. Such polarization contradicts the principles of sustainable city development. The findings indicated that the most pronounced deviations occurred not only in the aggregate SSP5 scenarios but also at the grid level, aligning with previous research [14,66].

Therefore, a thorough analysis of population estimates and distribution can significantly inform the development of climate change adaptation and mitigation strategies, including urban infrastructure planning. Hanberry [16] highlighted the scalable potential of innovative research methodologies focused on projected population data. A key strategy is population interpolation, facilitating the examination of projected population density categories and their interactions with various climate change facets. It is anticipated that enhancing this approach will involve its integration with detailed, grid-specific climate models, assessments of grid-specific climate vulnerability, and the inclusion of risk functions.

In conclusion, this study advocates for more stringent verification of population projections in regional urban planning, underscoring the importance of alignment with climate change adaptation and mitigation strategies.

5.2. Innovations and Challenges in Population Projection

We recognize the challenge that global scenarios predominantly remain at the national level. Specifically, the projection of population data, deeply intertwined with industry, land

use, ecology, and policy within SSP scenarios, requires precise execution [42,67]. We faced two main challenges: selecting a reliable SSP scenario for a mid-to-long-term horizon and generating refined population projections.

To overcome these challenges, we selected an appropriate SSP scenario for the Seoul area, adhering to international standards set by the global SSP (IIASA). Given that the latest IIASA data were from 2018, we aimed to bridge the population underestimation gap by integrating 2020 data from Statistics Korea, consistent with the 2020 baseline used in this study.

Moreover, we refined population projections by merging the cohort model with the dasymetric method and incorporating real population data, such as births, deaths, and migration, while enhancing granular population distribution forecasts. Notably, the micro-level application of the dasymetric method utilized total floor area data from residential buildings. Previous studies have commended the accuracy of building floor area data in applying the dasymetric method for population allocation [7,68], thereby improving the precision of spatial population density and distribution in the Seoul area.

Applying these data for medium-to-long-term forecasting can introduce temporal discrepancies between population figures and existing building footprints, potentially leading to inconsistencies between population and built-up area data, as highlighted by Wan et al. [7]. To address these challenges, we adopted a novel approach that integrates the temporal dimension. Specifically, we utilized data from before 2020 to account for population change trends from prior years up to the reference point, enabling an accurate reflection of the increase or decrease in new residential buildings. This was achieved by analyzing the accumulation and trends in residential building completion dates by grid from 2010 to 2020 and using this information as a weighting factor in our final analysis.

The methodological innovation of this study can be summarized as follows: Firstly, the use of total floor area data significantly improved the accuracy of our estimation results. Secondly, assuming the utility of total floor area for population estimation, we developed a method to express the trend of total floor area as a regression equation, enabling precise future population estimations at a micro-spatial level. Notably, building information, which is crucial for property rights, necessitates extensive public resources to achieve maximum accuracy. Thus, integrating precise and up-to-date building data with statistical data marks a substantial contribution to this field. Thirdly, integrating population estimation results derived from building data with SSP scenarios offers valuable insights for forecasting future demographic changes. This information serves as a crucial foundation for decision-making in areas related to carbon emission reduction efforts, thereby significantly contributing to addressing climate change challenges.

The limitations of this study are categorized into four areas. Firstly, as previously mentioned, grid-level population projections are time-bound, and the focus of this study is limited to Seoul, a highly urbanized capital city in Korea. Consequently, the study does not fully explore the complex characteristics of rural areas outside urban centers. The temporal analysis of population estimates up to 2100 considers trends only from 2010 to 2020, while the spatial analysis relies on building allocation weights from 2020. Wan et al. [7] found that long-term population forecasts for urban areas with high density showed less spatial variability than those for less dense rural areas, indicating the need for a more detailed exploration of this difference.

Specifically, considering that population changes are affected by various factors such as new developments, infrastructure projects, changes in school districts, and employment opportunities [2,69], the potential for errors in population forecasts may increase over longer periods. Secondly, while the majority of the population resides in residential buildings, a significant portion also inhabits commercial or industrial buildings. However, directly applying the premise that the residential population correlates proportionately with the total floor area of a building is not straightforward. Estimating the residential population within non-residential buildings warrants additional investigation. Moreover, when buildings serve both residential and non-residential purposes, isolating the residential

floor area becomes challenging without specific data on the residential portion. Future efforts could resolve these complexities by integrating tagging information in the building data to distinguish between residential and commercial areas. Furthermore, the premise that floor area directly correlates with population size has limitations, as it may not capture the nuanced characteristics of residential buildings. For example, a spacious apartment could accommodate a relatively small number of people. Addressing this discrepancy requires further research. Despite these challenges, this study specifically focuses on estimating the residential population, considering only residential buildings in the total floor area calculation.

While this study might integrate aspects of development planning, including population trends, incorporating these variables entails comprehensive deliberations on their inclusion, priorities, and potential impacts on long-term population projections. The detailed data analyzed herein provide a valuable foundation for future interdisciplinary collaborations or examinations of their interplay with development demands. Consequently, the annual refinement of these data will progressively enhance the findings and reliability of the study over time.

6. Conclusions

This study aimed to conduct population projection based on SSP scenarios, focusing on more refined units, to support sustainable urban planning. We conducted an analysis of population projections for Seoul, Korea, from 2020 to 2100, at the city, Sigungu, and grid levels.

The findings revealed several key insights along with a high level of accuracy (RMSE). When considering Seoul as a whole, SSP5 is projected to have the highest population (5,683,042) by 2100, while SSP3 is projected to have the lowest (2,344,075). At the Sigungu level, Songpa-gu emerges with the highest population (320,928), while Jung-gu has the lowest (49,169) based on SSP2. These disparities at the local level are associated with the current usage of the area (predominantly commercial or residential) and also significantly influenced by the physical area of the Sigungu.

Furthermore, this study explored population projection at the grid level, utilizing a spatiotemporal approach based on residential total floor area data. This allowed for a comparison of population distribution and patterns among SSP1, SSP2, SSP3, SSP4, and SSP5 scenarios by the year 2100, focusing on the 2020 standard grid. Notably, the grid-level population estimation for 2100 reveals that SSP5 exhibits the largest total population and the highest population per grid, with a maximum of 81,487 people. A pronounced polarization phenomenon, characterized by significant population differences among grids, is also observed.

These outcomes are pertinent to climate change considerations in mid-to-long-term urban planning. They hold considerable potential for future applications, particularly in the realm of urban sustainability, where precise population projection and the development and allocation of infrastructure tailored to that population are increasingly critical at both national and regional levels.

The data generated are invaluable for comparative analyses with other population projection datasets or as a foundational dataset for ongoing annual adjustments. Moreover, these results can serve as pivotal input data for the development of a regional climate change integrated model, in conjunction with RCP and other sector-specific scenarios such as industry, land use, and ecology, thereby offering insights into sustainable urban planning.

In future research endeavors, we plan to construct an integrated population model that combines RCP and SSP scenarios, incorporating variables that gauge the degree of urbanization by region. This will entail conducting population estimates that account for diverse scenarios by connecting the SSP variations at the grid level from this study with the degree of urbanization based on RCP. These efforts can go beyond a mere understanding of population fluctuations stemming from socioeconomic changes. They have the potential

to actively contribute to the formulation of relevant policies for future responses and the promotion of interdisciplinary collaboration.

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