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How well do gridded population estimates proxy for actual population changes? Evidence from four gridded data products and three population censuses for China

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Abstract

High-resolution gridded population estimates are increasingly used to support public health, disaster, and socio-economic research. These gridded data allow phenomena to be studied at a finer spatial scale than the usual survey or administrative data (spatialization) and with higher frequency than typical decadal census data allow (temporal interpolation). However, little is known about how accurately these gridded data follow actual changes in population. Therefore, we use China's census data for 2000, 2010, and 2020 to test predictive accuracy of four popular gridded population data products, conducting our tests at three spatial levels (county/district, prefectural city, and province). The gridded population data are accurate cross-sectional predictors at all three spatial levels, with less than five percent of variation unexplained. They far less accurately predict temporal changes in population, especially for disaggregated spatial units (counties and districts) where just one fifth of the variation in population changes is predicted by the gridded data. Predictive performance of gridded data for population changes has fallen substantially in the last decade. We illustrate how these inaccurate predictions could distort analyses that examine trends in spatial inequality. Overall, our results suggest that caution is required in using these gridded data products as proxies for the actual changes in local population.

JEL Codes

R12

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cross-sectional

time-series

Census

China

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I. Introduction

High-resolution gridded population estimates are increasingly used to support a wide range of research. These grids are more flexible than relying on administrative boundaries, as they are often one km² or smaller, and are available at higher frequency than census data (Xu et al. 2021). Since the first globally available Gridded Population of the World (GPW) introduced in 1995, many global or regional gridded population datasets have been produced, mirroring the growing role of remotely sensed data in socio-economic research.¹ These datasets provide gridded population information for different temporal and spatial scales, and have been widely used for disaster assessments and risk management (Opdyke, and Fatima 2024), for analyzing land use change (Balk et al. 2019), in public health research and management (Colón-González et al. 2023; Dodd et al. 2024), for analyzing ecological and environmental change (Jing et al. 2024, Dasgupta et al. 2024), and for other socio-economic research (Ma et al. 2024; Melchiorri et al. 2024; Zeng et al. 2024). A motivation for using these gridded data is that analyses should be inclusive, omitting no-one from consideration (Freire et al. 2020).

The accuracy of gridded population estimates relies on source data, spatialisation methods, and environmental features (Chen et al. 2020; Thomson et al. 2022). For example, some gridded products, such as WorldPop and GRUMP, generate population projections over time and space based on remotely sensed night lights data to model the spatial distribution of population (Lloyd et al. 2019; Ye et al. 2019; Liu et al. 2024). Yet the extant evidence is that luminosity data poorly extract demographic and socioeconomic characteristics in complex environments (Zhao et al. 2019; Gibson et al. 2021). For example, Pérez-Sindín et al. (2021) find that luminosity predicts worst in low density places with high forest cover, while Chen and Nordhaus (2015) find that DMSP nighttime lights data cannot detect dim lights in parts of Africa with low population density and low productivity. Specifically for China, Gibson et al. (2024) shows that satellite-detected luminosity data are about six-times more responsive to changes in build-up area in cities than for the same extent of built-up area in villages; hence, gridded data for non-urban areas are likely to be far less accurate than for urban areas.

A further concern is that luminosity data poor predict local changes in economic activity (which correlate with population change), even where the cross-sectional prediction is

¹ A non-exhaustive list includes the Global Rural-Urban Mapping (GRUMP) project, LandScan Population data, Global Urban Footprint (GUF), High-Resolution Settlement Layer (HRSL), WorldPop datasets, the Global Human Settlement Population Layer (GHS-POP), Global Resource Information Database (UNEP/GRID), OpenPopGrid, and the China Gridded Population (CnPop) datasets. Our quantitative review is in Section II.

good (Goldblatt et al, 2020; Sun et al. 2020; Asher et al. 2021). For example, Zhang and Gibson (2022) found the newest and most accurate satellite-detected luminosity data could account for about 60 percent of the cross-county variation in GDP in China, but only about one percent of the annual changes. Likewise, Dong et al. (2021) showed that the changes in luminosity data are inconsistent with the long-term changes in local population in China. These findings raise the question of whether some of these problems in the uses of luminosity data carry over into the gridded population estimates.

It is therefore important to test how well gridded population data predict temporal changes, which requires a setting with on-the-ground changes in population location. China provides a good setting for such a test because of shifting migration patterns from 2000-2010 to 2010-2020. In particular, population growth recently shifted from the largest urban areas towards smaller cities. As an example of this trend, one of three previous hotspots for inward migration, the Beijing-Tianjin region, is no longer a hotspot and Tianjin actually had fewer resident migrants in the 2020 census than in the 2010 census (Li et al. 2024). In contrast, for 2000 to 2010 the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Beijing-Tianjin were the main migration destinations (Cao et al. 2018). These shifts in choices of destination cities and migrant motivations (Wang and Zhang, 2022; White et al. 2024) have tended to favour smaller cities for quality of life reasons in the last decade (Li and Xiao, 2022; Yang et al. 2022), reflecting a new multipolar era of migration patterns (Cao et al. 2023).

In this paper we examine how accurately gridded population estimates can capture the sharp change in population locations in China over the last two decades. Existing studies have neither included a systematic review of the different gridded population products nor a comparison of their performance in predicting population change. Because the gridded data are used for both cross-sectional and time-series studies, we also compare predictive accuracy in these two dimensions. We use China's population census data (2000, 2010, and 2020) as a benchmark to examine whether four popular gridded population datasets are good predictors of population change. We conduct our tests at three spatial levels (county/district, prefectural city, and province) so that future users of these gridded data may be better informed about the spatial scale where these datasets can be best used as proxies for actual population change.

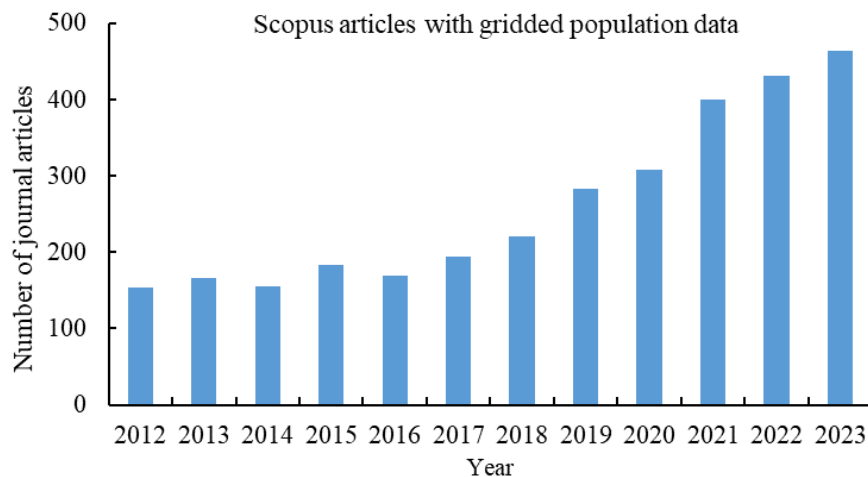
This paper is organized as follows: Section 2 reviews the application of gridded population datasets and discusses the main contribution of the study. Section 3 give the background of the changes in China's population migration patterns. Section 4 introduces the data sources, and the evaluation framework used in the analysis. Section 5 presents the

empirical results, comparing the prediction accuracy of multiple gridded population datasets at three administrative levels. Finally, Section 6 includes the main conclusions.

II. Literature Review

To provide quantitative evidence on the growing use of gridded population data in research in various disciplines we conducted a search in the Scopus database for journal articles that had any mention of GPW, GHS-POP, LandScan or WorldPop. About 150 articles per year were published using these gridded data products a decade ago but the output is now far higher, at about 500 articles per year (Fig 1). The growing use of these gridded data is particularly apparent in the field of environmental sciences, and earth and planetary sciences.

Figure 1. Annual output of articles using gridded population data



Notes: Search of Scopus database on 31 July, 2024. These are annual counts, rather than cumulative.

Amongst journal articles using gridded data products, several exploit the underlying cross-sectional variation in population density to study issues like accumulated ground heat (Benz et al. 2022), flood vulnerability (Yang et al. 2024), noise threshold values (Yasin and Alistair, 2019), and ecosystem services (Peng et al. 2024). These articles are especially prominent in the environmental science field, which is the discipline (under Scopus subject headings) that makes the most use of gridded population data. For example, using GPW data as a measure of population density, Unfried, Kis-Katos and Poser (2022), and Rathore et al. (2024) assessed the influence of irrigation expansion and water scarcity in Africa and the United States.

A reliance on the spatial variation in gridded population datasets is also seen in some of the economics studies using these data. For example, Dijkstra et al. (2022) use the WorldPop

data to provide a harmonized measure of global urbanization. Using the LandScan data and GPW data, Bosker et al. (2021) and Gollin et al. (2023) study agglomeration effects in Indonesia and Africa. González et al. (2023) used GPW data in their study of regional favouritism in Argentine districts and its impact on economic development. These population datasets are also used for modelling studies that aim to extend infrastructure to the unreached; for example, Oughton et al. (2023) used WorldPop data to evaluate the necessary investment requirements to achieve affordable universal broadband.

Studies relying on cross-sectional variation make up the majority of articles using gridded population estimates but there are also studies of *changes*, which inherently rely on the time-series variation. For example, Muhwezi et al. (2021) use the WorldPop estimates of annual population changes to explore drivers of rising electricity consumption in Kenya from 2010 to 2015. Maldonado (2023) studied rural poverty trends from 2000 to 2020 for states and municipalities in Venezuela, using annual gridded population and luminosity datasets. Likewise, gridded data are used by Patias et al. (2022) to study socioeconomic inequalities at various geographical levels in Britain for a 40-year period from 1971 to 2011. The changing flood risks due to hurricanes in Puerto Rico are studied using annual population density grids from WorldPop estimates for 2005 to 2016 (Archer et al. 2024). Changes in CO₂ emissions and air pollution are related to changing population density in GHS-POP and GPW gridded estimates (Castells-Quintana et al. 2021; Wilmot et al. 2024). Likewise, annual gridded population density estimates from WorldPop are used by Joseph (2022) to estimate impacts of the 2010 earthquake in Haiti on economic growth and recovery while Bourget et al. (2024) used GPW data to provide climate change risk assessments of pluvial flooding for insurance portfolios for Canada and the United States.

In summary, rapid advancement of remote sensing has enabled a profusion of gridded population estimates, which are increasingly used in different research fields. Our quantitative review suggests that WorldPop and GPW are the most widely used gridded data products, due to their wide coverage, ease of use (and the annual frequency for WorldPop facilitates study of short-term changes). GHS-POP estimates are also widely used, partly due to their fine spatial resolution (100m), and the annual frequency of LandScan estimates also make them a popular data source. However, little attention has been paid to the accuracy of these gridded products, particularly for studying time series changes, which motivates our interest to test how well the gridded population datasets can predict the actual population changes over time, at different spatial scales.

III. The test setting: China’s changing spatial population distribution

China is a useful setting for testing the accuracy of the gridded data products because over the last several decades it is home to the largest migration flow in history (Gu et al. 2020; Niu, 2022). In 1955, China established an internal registration (“Hukou”) system, to control rural migration to urban areas (Chan 2009); this produced a population that was both too rural and too inland to take advantage of new economic opportunities in coastal regions after China’s reform and opening up in 1978 (Shi et al. 2024). Once mobility controls were less stringently enforced, a massive population flowed out of the relatively underdeveloped central and western provinces (Zhou et al. 2024). Taking advantage of convenient transport facilities and information channels, the scale of population migration has increased in the past decade (Yang et al. 2022). As of China’s Seventh National Census in 2020, 376 million people were living in a different prefecture than their place of registration (inter-provincial 125 million, intra-provincial 251 million) (Cheng and Duan, 2021). Compared to the sixth census in 2010, this is a significant increase of 155 million (almost 70% growth) more migrants.

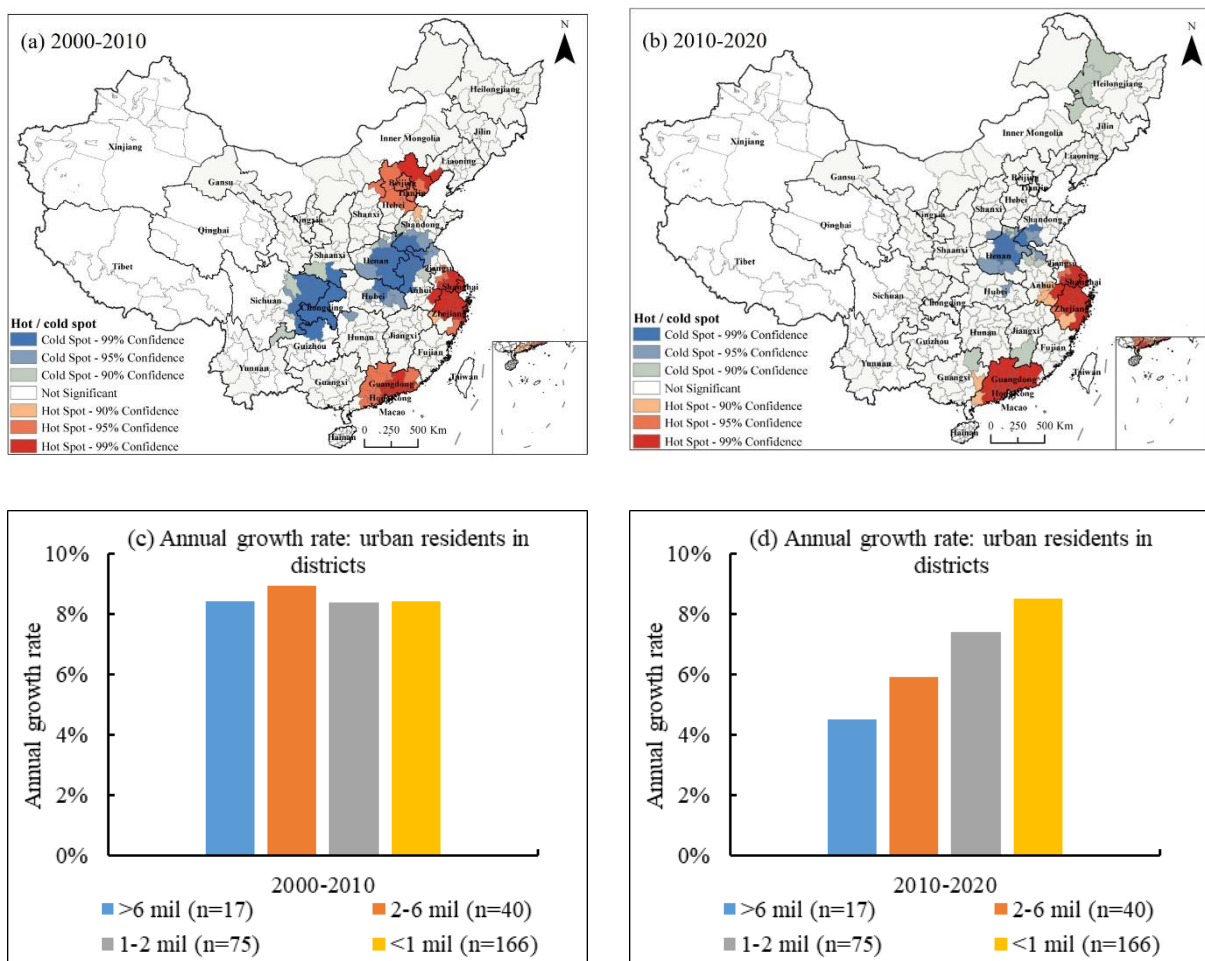
Adding to the advantage of using China to test the predictive accuracy of gridded population products is a sharp change in destinations of this migrant flow, from 2000-2010 to 2010-2020. In the earlier decade, the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Beijing-Tianjin-Hebei regions were all hot spots for inward migration, while cold spots (sources for outward migration) were less developed central regions such as Chongqing and parts of Henan, Anhui, and Sichuan provinces (Figure 2a). This pattern changed in the most recent decade, with the Beijing-Tianjin-Hebei region ceasing to be a migration hotspot (in fact the 2020 census recorded fewer migrants in Tianjin than there were in 2010). The cold spots also receded to mainly be centered on Henan (Figure 2b).

These changes in the origins and destinations of the migrant flows from 2000-2010 to 2010-2020 are also seen in changes in the patterns of population growth rates by city size category (Figures 2c and 2d).² Between 2000 and 2010 large cities and small cities all grew at about the same rate of eight percent per annum; notably this growth is almost entirely due to migration rather than natural increase and so it implies that cities across a range of sizes were equally attractive to migrants (thresholds for the size categories are chosen to roughly double

² The spatial units in panels a and b of Figure 2 are prefectural-level cities, but these are not ‘cities proper’ because they often include low density, largely rural, counties. In contrast, the units in panels c and d of Figure 2 are ‘districts’ (or *shiqu*); these are one of three types of 3rd level sub-national units and have a mean population density that is almost ten-times higher than for counties, which are the other common 3rd level unit.

the number of cities in the next group when moving down one category). However, the most recent decade saw the largest cities (with > 6 million residents) growing at only one-half the rate of the smallest cities (with < 1 million residents). Instead of migrants going into the big urban areas like Beijing-Tianjin they were increasingly moving to smaller cities. These sharp changes in the sources and destinations for migration flows, and the consequent changes in the patterns of population growth rates by city size should provide a challenging test for the ability of the gridded population products to predict these on-the-ground changes.

Figure 2. Hot/cold spots of China’s net migration (panels a and b) and population growth rates by city size category (panels c and d), by decade



IV. Data and Methods

Data Source

We use census data (and GDP for the inequality analysis) for all of the parts of China that are organized as prefectural-level cities (rather than other 2nd level units, such as banners). This covers more than 94% of China’s resident population according to the seventh population

census in 2020. In this sample there are a total of 31 provinces, 297 prefectural-level cities, and 2851 county-level units (districts, counties, and county-level cities). The analyses are carried out at all three spatial levels, to test whether the predictive performance of the gridded data varies with the level of spatial aggregation.

Most gridded datasets use dasymetric models to estimate the spatial distribution of population, combining census data with other spatial data (e.g., land cover) to disaggregate population counts across grid cells. The “top-down” approach spreads population counts into small grid cells, as used, for example, by GHS-POP. Simple top-down approaches assume a uniform distribution of population within spatial units (e.g., GPWv4), while more complex approaches incorporate ancillary data (e.g., land cover, night-time lights) to generate weights for allocating population. In contrast, “bottom-up” approaches typically rely on micro-census samples and build geo-statistical relationships between micro-census population density and the built environment to predict population counts across grid cells of unsampled areas (e.g., LandScan). Considering the availability and diversity of the gridded population datasets, we chose the GPW, GHS-POP, WorldPop, and LandScan data to evaluate the performance of gridded population data sets in capturing the changes in population patterns. The census data for 2000, 2010, and 2020 are used as the benchmark. Table 1 presents some characteristics of the four gridded population datasets that we work with.

The GPW dataset, developed by the NASA Socioeconomic Data and Applications Center (SEDAC), is now in its fourth version (GPW4). This data product has gridded data on total population counts and densities and other key demographic variables, globally at a nominal spatial resolution of 1 km. In contrast, WorldPop was developed collaboratively by multiple organizations and institutions to meet needs of a wide range of users. In this study we used the unconstrained individual country UN adjusted population count from the WorldPop dataset with a spatial resolution of 100-m for 2000, 2010, and 2020.

The Global Human Settlement Population Grid (GHS-POP) is the latest released global gridded population dataset based on remotely sensed data developed by the EU Joint Research Centre, and this depicts the distribution and density of the total population as the number of people per grid cell (Schiavina et al. 2023). Finally, we also use the LandScan dataset for 2000, 2010, and 2020, obtained from the Oak Ridge National Laboratory (ORNL), and providing a high-resolution global population distribution dataset that has been used for a wide range of applications (Sims et al. 2023). Leveraging state-of-the-art spatial modelling techniques and advanced geospatial data sources, LandScan provides detailed information on

population counts and density at a 30 arc-second resolution (ca. 1 km²), enabling precise and up-to-date insights into human settlement patterns across the globe.

Table 1. Summary of gridded population datasets used in this study

Datasets	WorldPop	GPWv4.11	GHS-POP	LandScan
Temporal range	2000-2020	2000, 2005, 2010, 2015, 2020	1975-2020	1998 and 2000-2019
Resolution	100 m	1 km	100 m	1 km
Coverage	Global	Global	Global	global
Frequency	Annual	Every 5 year	Every 5 year	Annual
Predictor variables	Roads, Land Cover, Built structures, NTL, Infrastructure, Environmental data, Water Bodies	Water Bodies	Built structures	Roads, Land Cover, Built structures, Infrastructure, Environmental data, Water Bodies
Sources	WorldPop, University of Southampton	SEDAC	GHSL project	ORNL
Access Link	https://www.worldpop.org/	https://sedac.ciesin.columbia.edu/	https://www.resdc.cn/	https://landscan.ornl.gov

Note: GPW is Gridded population of the world, SEDAC is the Socioeconomic Data and Applications Center, RESDP is Resource and Environmental Science Data Platform, ORNL is the Oak Ridge National Laboratory, GHS is Global Human Settlement, GHSL is the Global Human Settlement Layer.

Estimation Framework

To test the predictive accuracy of gridded population estimates the following regression model is used, where it is estimated separately at county-level, prefectural city level, and at province level, and separately for each of the four gridded data products:

$$\ln(\text{census_pop})_{it} = \alpha + \beta \ln(\text{grid_pop})_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

where the i indexes cross-sectional units; the t indexes years; the μ_i are fixed effects for each cross-sectional unit; the φ_t are fixed effects for each year; and ε_{it} is the disturbance term. The parameters of greatest interest are β , the elasticity of census population with respect to the gridded population estimate, and also the R^2 values showing the predictive performance. The fixed effects control for the influence of unobserved time-invariant features of each cross-sectional unit, and the influence of spatially-invariant features of each time period. The equation is estimated with a 3-period panel, using data for 2000, 2010, and 2020.

The estimation framework allows two different types of elasticities and R^2 which relate to the cross-sectional and time-series variation in panel data. If equation (1) is averaged over time, we get:

$$\overline{\ln(census_pop)}_i = \beta^B \overline{\ln(gridded_pop)}_i + \mu_i + \bar{\varepsilon}_i \quad (2)$$

where time-averaged values of (log) census population and gridded population are used in a cross-sectional Ordinary Least Squares regression, to yield β^B , the *between estimator*. The relationship in equation (2) refers to the long-run and shows how well time-averaged gridded data might predict the location of the population.

The second type of elasticity, β^W , is the *within estimator*, where the variation over time within each cross-sectional unit provides the basis for estimating:

$$\begin{aligned} \ln(census_pop)_{it} - \overline{\ln(census_pop)}_i = \\ \beta^W [\ln(gridded_pop)_{it} - \overline{\ln(gridded_pop)}_i] + \varepsilon_{it} - \bar{\varepsilon}_i \end{aligned} \quad (3)$$

Equation (3) is based on subtracting equation (2) from equation (1); in doing so it removes effects of spatially invariant fixed effects (e.g. topography). Note that equation (3) provides equivalent estimates to what would be obtained by estimating equation (1) with separate intercepts for every cross-sectional unit. The within estimator allows examination of the time-series fluctuations in population within areas and specifically provides a basis for assessing how well gridded estimates can predict *changes* in the location of population. Further details on the within and between estimators can be seen in Zhang and Gibson (2022).

The within estimator is based on the changes in population from 2000 to 2010, and from 2010 to 2020, for the same places. However, it does not allow a direct comparison of the predictive performance in these two decadal sub-periods, so we also use the following regression, where $T=1$ for the second decade and zero otherwise:

$$\Delta(census_pop)_{it} = b_0 + d_0 * T + b_1 T * \Delta(gridded_pop)_{it} \quad (4)$$

This equation allows a Chow test to be estimated, for whether there is a change between the 2000-2010 period and the 2010-2020 period, in the degree of predictability of the changes in population between censuses, using the changes in the gridded population estimates as the predictor variable.

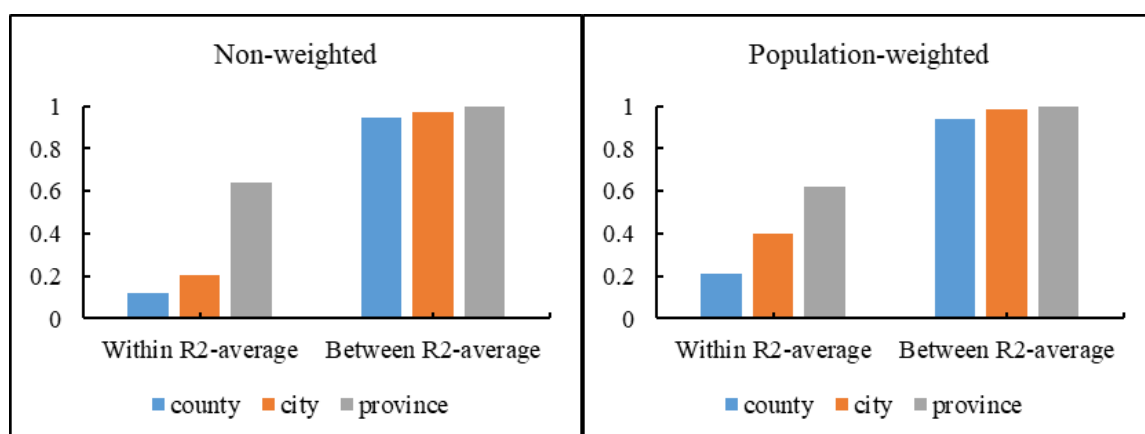
V. Results

Within and Between Estimator Results at Three Aggregation Levels

Tables 2-4 have within and between estimator results, using (log) census population in 2000, 2010 and 2020 as the dependent variable, and the four sets of gridded population estimates (WorldPop, GPW, GHS, and Landsat) as the predictor variables. The results for each administrative level (county-level units, prefectural cities, and provinces) are each in their own table, with within estimator results presented first and then the between estimator results. We also present population-weighted results in case impressions about predictive accuracy are affected by patterns for spatial units with not many people, noting the large imbalance in the population density between eastern and western regions of China.

We begin with a figure that summarizes patterns of predictive performance as the level of spatial aggregation changes. In order to reduce clutter, the R^2 values from each model for each gridded data product are averaged, because spatial aggregation patterns are common across the four data products. The level of spatial aggregation does not make much difference to the predictive performance for the between estimator, with R^2 values close to 1.0 at the county, prefectural city and province level (the values rise slightly, from 0.95 to 0.99, using the unweighted results). However, for the within estimator, predictive performance of the gridded data, in accounting for inter-census changes in population, gets much worse as spatial scales become more local. Specifically, the average within R^2 at the county level is just 0.12 (using the unweighted regressions, or 0.21 using population-weighted regressions). Average within R^2 values are somewhat higher, at about 0.2 (unweighted) or 0.4 (weighted) at the prefectural-city level, and are higher still, at about 0.6, at the province level.

Figure 3. Averages of the within-R-squared, and between-R-squared (averaging over four models, one per gridded population product) by three spatial aggregation levels.



The poor predictive performance for population changes from gridded estimates at the county local level is concerning because gridded estimates are especially used as a proxy for changes in local population. There are other sources of population estimates at provincial level in the years between a census; for example, surveys have representative samples at this aggregation level even if they are not representative at county-level for all counties. So, the gridded data are rather less needed for provincial level analyses and much more needed for county-level or even more local level analyses. Therefore, neither the good predictive performance for gridded data in cross-sectional analyses nor a reasonable predictive performance (with R^2 values of about 0.6) for time-series changes at the provincial level are relevant to the poor performance in predicting changes in population at the most local levels.

Turning to the detailed regression results at the county-level (Table 2), within- R^2 values are about one-eighth of the between- R^2 although the use of population weights raises the predictive performance of the within estimator. To be specific, the within- R^2 values are about 0.1 (unweighted) and 0.2 (weighted), while between- R^2 values are all higher than 0.9. Within estimator elasticities from three of the gridded datasets are relatively similar (slightly higher for GHS-POP) at around 0.7 but are far lower for LandScan at around 0.4. In contrast, the between elasticity values are more alike for all four gridded population datasets (ranging from 0.96 to 0.98), which is much higher than the within estimator elasticities.

The prefectural city-level populations are more predictable, both cross-sectionally and for time-series changes. The basic pattern of the between- R^2 being higher (by up to five times) than the within- R^2 still holds. The elasticities are also higher, especially for the within estimator, where they are above 0.9 for WorldPop and GHS-POP (but are only from 0.6-0.7 for LandScan). Also, unlike the pattern in the county-level results, using population weights does not raise within estimator elasticities although it does approximately double the within- R^2 values, to around 0.4. In terms of cross-sectionally predicting the locations of census populations, the between- R^2 values all exceed 0.96 and the elasticities are close to 1.0.

The gridded data have their highest predictive accuracy at the provincial level, with the within- R^2 values ranging from 0.55 to 0.7. At this level, population weighting makes little difference (the variation is much less than at the 3rd subnational level). The GHS-POP data have the closest relationships with changes in census population, with elasticities of 0.70 (unweighted) or 0.67 (weighted) while LandScan data has the weakest relationships and the

lowest elasticities. However, even at this aggregation level, the time-series relationships for population changes are far weaker than the cross-sectional ones (Table 4).

Table 2 (a). Relationships between gridded population datasets and census population: within and between estimator results (2814 county-level units, non-population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each county				
ln(pop_grid)	0.683*** (0.043)	0.691*** (0.043)	0.797*** (0.040)	0.388*** (0.024)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.113	0.114	0.140	0.118
Between-estimator, for average pop differences between counties				
ln(pop_grid)	0.972*** (0.004)	0.972*** (0.005)	0.965*** (0.004)	0.976*** (0.005)
R-squared (Between)	0.959	0.940	0.949	0.937

Table 2 (b). Relationships between gridded population datasets and census population: within and between estimator results (2814 county-level units, population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each county				
ln(pop_grid)	0.774*** (0.034)	0.780*** (0.034)	0.805*** (0.036)	0.418*** (0.026)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.212	0.214	0.208	0.210
Between-estimator, for average pop differences between counties				
ln(pop_grid)	0.960*** (0.004)	0.957*** (0.004)	0.957*** (0.004)	1.005*** (0.006)
R-squared (Between)	0.947	0.943	0.942	0.913

Table 3 (a). Relationships between gridded population datasets and census population: within and between estimator results (297 prefectural city-level units, non-population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each city				
ln(pop_grid)	0.915*** (0.086)	0.876*** (0.080)	0.957*** (0.099)	0.677*** (0.078)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.226	0.205	0.173	0.210
Between-estimator, for average GDP differences between cites				
ln(pop_grid)	0.973*** (0.007)	0.978*** (0.010)	0.994*** (0.009)	1.012*** (0.012)
R-squared (Between)	0.983	0.973	0.977	0.963

Table 3 (b). Relationships between gridded population datasets and census population: within and between estimator results (297 prefectural city-level units, population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each city				
ln(pop_grid)	0.864*** (0.072)	0.866*** (0.072)	0.967*** (0.081)	0.629*** (0.093)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.443	0.442	0.366	0.338
Between-estimator, for average pop differences between cites				
ln(pop_grid)	1.004*** (0.006)	1.004*** (0.006)	1.012*** (0.007)	1.033*** (0.012)
R-squared (Between)	0.990	0.988	0.987	0.963

Table 4 (a). Relationships between gridded population datasets and census population: within and between estimator results (31 provincial -level units, non-population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each province				
ln(pop_grid)	0.673*** (0.061)	0.674*** (0.060)	0.837*** (0.088)	0.777*** (0.066)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.649	0.661	0.701	0.546
Between-estimator, for average pop differences between provinces				
ln(pop_grid)	1.007*** (0.007)	1.039*** (0.012)	1.028*** (0.009)	0.991*** (0.016)
R-squared (Between)	0.999	0.996	0.997	0.993

Table 4 (b). Relationships between gridded population datasets and census population: within and between estimator results (31 provincial -level units, population weighted).

Dependent variable: ln(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
Within-estimator, for annual pop changes within each province				
ln(pop_grid)	0.718*** (0.095)	0.718*** (0.095)	0.870*** (0.123)	0.744*** (0.053)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.654	0.656	0.666	0.588
Between-estimator, for average pop differences between provinces				
ln(pop_grid)	1.018*** (0.009)	1.025*** (0.010)	1.020*** (0.008)	0.992*** (0.022)
R-squared (Between)	0.998	0.997	0.998	0.986

Regression Results for Population Changes

The results in Tables 2-4 consistently show the gridded data products are far better predictors for cross-sectional analysis than for time-series studies where variation comes from changes in population. In this section we drill down into the time-series variation by using regressions to test if there has been a decline over time in the predictive performance for the population changes. Specifically, we test whether the predictions of changes in population became less accurate from 2000-10 to 2010-20. We carry out this test at the county/district level, at the prefectural city level, and at the provincial level.

Consistent with Table 2, that shows predicting inter-census changes in county-level population is the task that the gridded population estimates do least well, the R^2 values in Table 5(a) for the county-level population changes show that only a small percentage of the variation is predicted by the changes in the gridded data. Specifically, for the first decade the R^2 averages 0.53 for three gridded products (WorldPop, GPW and GHS-POP) and is even lower, at just 0.31, for LandScan. There was a sharp fall in predictive accuracy in the second decade, for changes from 2010 to 2020, with R^2 values that average just 0.10. This substantial weakening in the relationship is also shown in the coefficients, which fell from around 1.2 to just 0.5 for WorldPop, GPW and GHS-POP, and from about 0.6 to about 0.4 for LandScan. Ideally for the specification we use, coefficients would be close to 1.0, so that each extra person in a county by next census date that is suggested by the gridded population product is matched with an actual extra person in that same place according to the two censuses.

For the results at the prefectural city level, in Table 5(b), the coefficients in the first decade were close to the ideal value of 1.0 for WorldPop, GPW and GHS-POP, but they fell to being only two thirds as large in the second decade. For LandScan the fall in coefficients was from 0.84 to 0.75. Likewise, the R^2 values for the first three gridded products fell from 0.65 to the 0.2-0.3 range (while for LandScan they stayed just over 0.3 for both decades). So, even at the more aggregated level there was a decline in predictive performance. These falls also show up in the Chow tests, which suggest that regressions for the 2010-to-2020 decade are significantly different to the regressions for the earlier decade.

At the provincial level, the regressions using WorldPop, GPW or GHS-POP had coefficients and R^2 values close to 1.0 for the population changes from 2000 to 2010. Yet for the second decade the R^2 values had fallen by about one-half. Moreover, the coefficients suggested that the gridded data were overstating population change (each one extra person in a gridded dataset results in just 0.8 extra persons in the census data for 2020).

Table 5 (a). Relationships between changes of gridded population datasets and census population: 2000-2010 versus 2010-2020 (2814 county-level units).

Dependent variable: d(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
	pop changes from 2000 to 2010			
d(pop_grid)	1.232*** (0.022)	1.260*** (0.022)	1.244*** (0.022)	0.563*** (0.016)
R-squared	0.527	0.532	0.531	0.307
	pop changes from 2010 to 2020			
d(pop_grid)	0.517*** (0.026)	0.501*** (0.025)	0.412*** (0.027)	0.394*** (0.020)
R-squared	0.120	0.127	0.076	0.120
Chow test	28.02***	32.52***	70.25***	1.15

Table 5 (b). Relationships between changes of gridded population datasets and census population: 2000-2010 versus 2010-2020 (297 city-level units).

Dependent variable: d(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
	pop changes from 2000 to 2010			
d(pop_grid)	0.940*** (0.041)	0.962*** (0.041)	0.952*** (0.041)	0.837*** (0.070)
R-squared	0.641	0.647	0.646	0.326
	pop changes from 2010 to 2020			
d(pop_grid)	0.619*** (0.053)	0.605*** (0.049)	0.648*** (0.078)	0.745*** (0.063)
R-squared	0.315	0.337	0.185	0.323
Chow test	3.39*	4.43*	2.12	0.08

Table 5 (c). Relationships between changes of gridded population datasets and census population: 2000-2010 versus 2010-2020 (31 provincial -level units).

Dependent variable: d(pop_census)	Gridded population dataset			
	WorldPop	GPW	GHS-POP	LandScan
	pop changes from 2000 to 2010			
d(pop_grid)	1.038*** (0.023)	1.058*** (0.018)	1.047*** (0.019)	0.866*** (0.112)
R-squared	0.985	0.991	0.990	0.660
	pop changes from 2010 to 2020			
d(pop_grid)	0.771*** (0.144)	0.784*** (0.123)	0.986*** (0.200)	0.845*** (0.157)
R-squared	0.479	0.570	0.438	0.483
Chow test	1.79	3.49*	0.03	0.01

Note: The Chow test results for the difference in the models between the two periods is shown in the last row, with statistical significance at the 1%, 5% and 10% level denoted by ***, **, *.

An Example: How Gridded Population Data Distort Apparent Trends in Spatial Inequality

The results thus far suggest that the gridded population datasets may be useful for spatialization but are less useful for studies that involve population changes, especially at the most local level. In this section we provide an example of how an analysis may go astray when changes in the gridded population estimates are used as a proxy for changes in actual population. The example concerns spatial inequality, which is an ongoing subject of study in China (Zhang et al., 2023) where population estimates are needed as the weight for constructing inequality statistics from the annual data on local GDP (essentially comparing shares of income versus population at the various quantiles). Chen (2025) is an example of just such a study, estimating trends in spatial inequality in China over the last two decades by combining county-level annual GDP data with LandScan annual gridded population estimates.

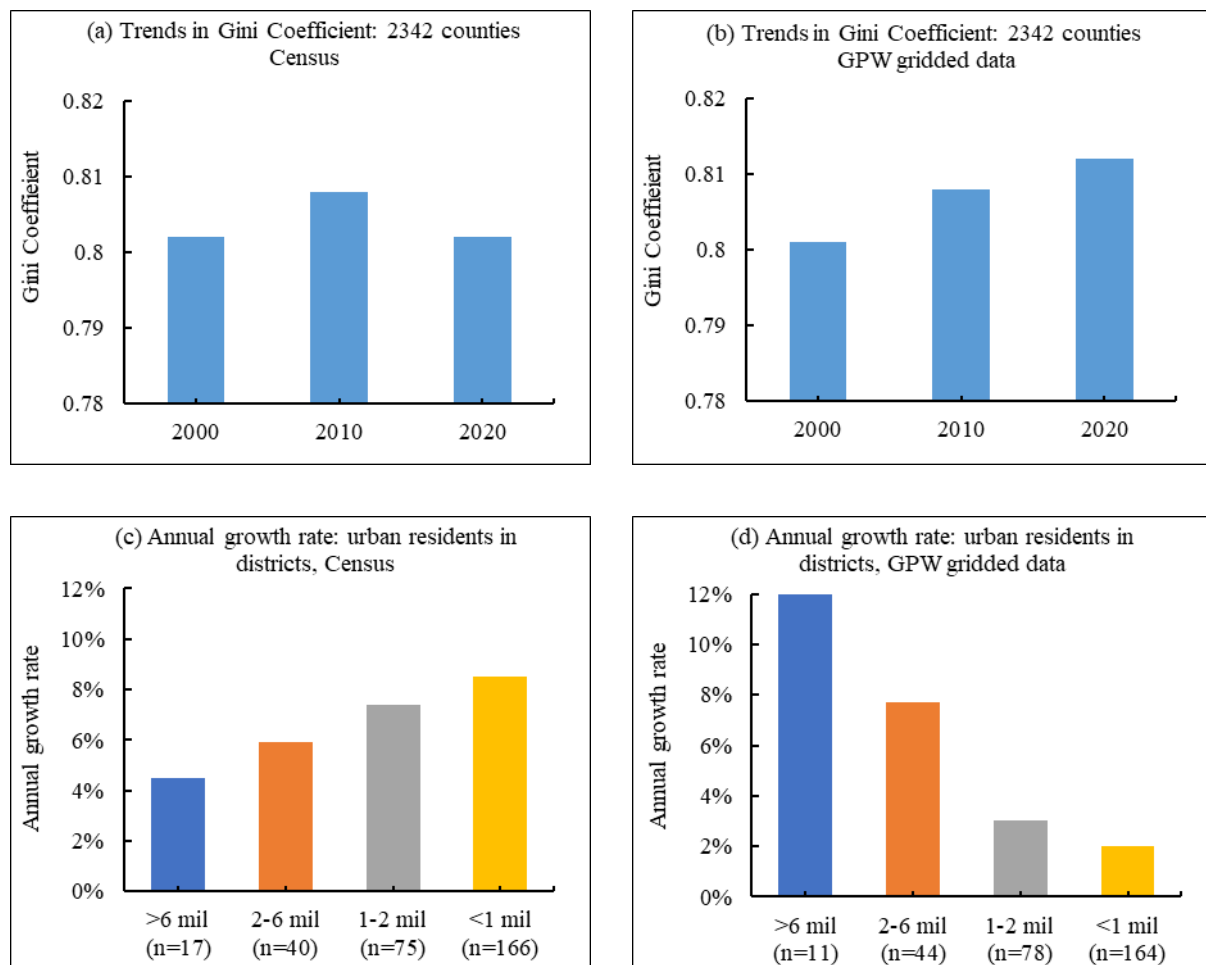
In order to present the gridded population estimates in the best possible light we use the GPW estimates that had the best predictive performance at the county level in Table 5(a). The county-level GDP data and census counts for 2000, 2010, and 2020 are used to estimate a Gini index of inequality.³ We then repeat the calculations using GPW gridded data aggregated to the county level. When the census data are used it is apparent that there was a rise in inequality from 2000 to 2010, that then reversed between 2010 and 2020 with the Gini index returning to the initial value (Figure 4(a)). In contrast, when the GPW estimates are used there appears to be an ongoing rise in spatial inequality, with the Gini index always higher than in the previous census year (Figure 4(b)). In other words, the gridded data product gives the impression that spatial inequality in China has continued to rise over the most recent decade which distorts the patterns shown by the actual population counts from the census.

One explanation for this distortion of the spatial inequality trends is that the GPW estimates miss the sharp change in patterns of population growth rates according to city size. The bar chart in panel (c) of Figure 3 reproduces the annual population growth rates for urban districts (the high-density parts of prefectural level cities) calculated from the 2010 and 2020 census counts. Recall that prior to 2010 the large and small urban districts were all growing at a rate of about eight per cent per year, but from 2010 to 2020 the most populated urban districts had growth rates just one-half as fast as for the least populated ones, as the migrant destinations

³ One difference from the analyses in Tables 2 and 5 is that the county-level GDP data for individual districts that are adjacent to each other within the core urban area of a prefectural city have their GDP reported as a single entity rather than on a district-by-district basis in the statistical yearbooks we use; these aggregations are why the sample size falls to n=2342 county/district-level units from the previous n=2814 sample size.

shifted away from big cities to smaller urban areas. This shift has impacts on spatial inequality because the previous migration hotspots like the Beijing-Tianjin region had higher GDP per capita than other migration destinations and so spatial inequality rose as these regions gained population. In contrast, in the most recent decade spatial inequality fell as population growth shifted towards smaller cities, with lower per capita GDP, because of the changes in migration patterns.

Figure 4. The comparison between census population and gridded population datasets.



The last figure, in panel (d) shows that the gridded population estimates miss this sharp change in the patterns of population growth rates. Rather than the largest cities (urban districts with more than six million residents) having annual population growth rates that were only half as fast as for the smallest (< 1 million residents) districts – what the census data show – the gridded estimates suggest that the most highly populated urban districts were growing far faster than the least populated ones. Consequently, the rise in spatial inequality that was shown with the census data from 2000 to 2010 is incorrectly shown to have continued on into the 2010-20 decade because the gridded population estimates miss the sharp change in migration patterns.

VI. Conclusions

With the development of remote sensing technology, several recent efforts have produced global- and continental-extent gridded population estimates. These data are available at fine spatial scales, with grid sizes of 1 km or smaller, and are often updated with annual frequency. In contrast, actual population counts from censuses are often available just once per decade and may have publicly available data only disaggregated down to the county/district level so study at very local levels may be limited. Given these constraints, the gridded population estimates appear to be an attractive data source, which may account for growing use of these data in various branches of research. While our review suggests that more of the studies using these data rely upon their spatialization aspects (and so cross-sectional accuracy matters), there are also a growing number of studies that rely on estimated population changes, and in this case the time-series accuracy of these gridded estimates matters.

In this paper, we examined how well the gridded population estimates can predict the differences in census population between places and between time periods. Our testing used a set of regression analyses, with four popular sources of gridded population estimates used to predict census counts for China in 2000, 2010, and 2020, at three subnational administrative levels: county/district, prefectural level city, and province. Our key finding is that gridded data are better at predicting cross-sectional population differences than at predicting the changes in population over time, especially at the most local level. For example, at the county level, most of the temporal variation in the changes in population is not predicted by changes in the gridded estimates; only about ten percent is predicted using the unweighted regressions, or 20 percent using population-weighted regressions. In contrast, at this same spatial level, about 95 percent of cross-sectional variation in census population is predicted by the gridded estimates. It also seems that the predictive performance for temporal changes has fallen over time, being worse for changes in the most recent decade compared to the prior decade.

The predictive performance for temporal changes in population is better at higher levels of the subnational administrative hierarchy, such as prefectural level cities and provinces, but at these higher levels – especially for provinces – there are other sources of annual population estimates in the years between a census, such as from sample surveys. Hence, weak predictive performance of gridded population estimates is especially a problem for the type of spatially disaggregated units where the gridded data would seem most useful given that other data may not be available at the same 1 km (or smaller) scale. Moreover, even for the higher-level spatial units, there was a clear decline in predictive performance in the most recent decade.

Although our study is only focused on China, there are broader implications for the uses of these gridded population products in research. If a research design is based on temporal variation in the subject under study, relying on gridded population estimates may be a source of vulnerability, especially if the locations of population change have shifted sharply, as they did for China between the most recent decade and the prior decade. For example, where there is a large-scale migration underway in the presence of substantial regional disparities in living standards, population movements will also be associated with changes in spatial inequality. To the extent that the gridded estimates miss some of the on-the-ground changes they may give a misleading impression about the trends in spatial inequality and could lead to inappropriate policy interventions that are based on a misreading of the actual situation. Overall, our findings suggest that researchers should be cautious in relying on gridded population estimates as a proxy for the actual temporal changes in population that are occurring at fine spatial scales.

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