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LETTER

Spatiotemporal dynamics of global population and heat exposure (2020–2100): based on improved SSP-consistent population projections

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Abstract

To address future environmental change and consequent social vulnerability, a better understanding of future population (FPOP) dynamics is critical. In this regard, notable progress has been made in producing FPOP projections that are consistent with the Shared Socioeconomic Pathways (SSPs) at low resolutions for the globe and high resolutions for specific regions. Building on existing endeavors, here we contribute a new set of 1 km SSP-consistent global population projections (FPOP in short for the dataset) under a machine learning framework. Our approach incorporates a recently available SSP-consistent global built-up land dataset under the Coupled Model Intercomparison Project 6, with the aim to address the misestimation of future built-up land dynamics underlying existing datasets of future global population projections. We show that the overall accuracy of our FPOP outperforms five existing datasets at multiple scales and especially in densely-populated areas (e.g. cities and towns). Followingly, FPOP-based assessments of future global population dynamics suggest a similar trend by population density and a spatial Matthew effect of regional population centralization. Furthermore, FPOP-based estimates of global heat exposure are around 300 billion person-days in 2020 under four SSP-Representative Concentration Pathway (RCPs), which by 2100 could increase to as low as 516 billion person-days under SSP5-RCP4.5 and as high as 1626 billion person-days under SSP3-RCP8.5—with Asia and Africa contributing 64%–68% and 21%–25%, respectively. While our results shed lights on proactive policy interventions for addressing future global heat hazard, FPOP will enable future-oriented assessments of a wide range of environmental hazards, e.g. hurricanes, droughts, and flooding.

1. Introduction

In recent years, five Shared Socioeconomic Pathways (SSPs) were proposed by the Intergovernmental Panel on Climate Change for navigating the uncertainties in addressing future climate change (Riahi et al 2017) and advancing our common journey toward sustainability (Szetey et al 2021). Essentially, SSPs 1–5 depict five plausible future scenarios of socioeconomic development (Kriegler et al 2014) which can be used to derive greenhouse gas emissions scenarios with different climate policies. SSPs 1–5 correspond respectively to sustainability (SSP1), middle of the road (SSP2), regional rivalry...
(SSP3), inequality (SSP4), and fossil-fueled development (SSP5), and have been gaining increasing popularity within the global change and sustainability research community (Maury et al. 2017, Van Vuuren et al. 2017). These SSPs are distinguished by a few socioeconomic variables (e.g. population, GDP, urbanization, and education level). Among these fundamental variables, particularly, the arguably most critical is population. Population data are often the basis for addressing a wide range of social concerns, e.g. epidemics (Coccia 2020), heat waves (Liu et al. 2017, Huang et al. 2019), floods (Gu 2019), droughts (Liu and Chen 2021), and sea-level rise (Kulp and Strauss 2019), and for monitoring 73 indicators of the UN SDGs (Freire et al. 2018) that require population data as an input (Dahmm 2021). In this vein, an urgent need is to downscale the projection of future global population over the 21st century to spatially explicit projections—i.e. to produce SSP-consistent gridded population data.

Notable progress has been made in producing such SSP-consistent gridded population projections at the global and regional scales. For global projections, Jones and O’Neill (2016) at the National Center for Atmospheric Research (NCAR) developed a widely-used global population dataset under SSPs 1–5. They predicted grid-level population under the SSPs’ constraints of population and urbanization. Yet, the dataset was found that approximately 30%–43% of the estimated population were in uninhabited areas with cropland, forest, or pasture in 2050 (Chen et al. 2020c) and is limited by its relatively low resolution (i.e. 0.125 degree). Subsequently, Gao (2020) down-scaled the NCAR dataset from 0.125 degree to 1 km. There are other global forecasting efforts, albeit similarly they suffer from low resolution, poor accuracy for certain areas, and/or sometimes considering only partial SSPs (Murakami and Yamagata 2019). For regional projections, high-resolution gridded population datasets under the SSPs have been developed for Africa (1 km) (Boke-Olén et al. 2017), China (1 km (Chen et al. 2020a) and 100 m (Chen et al. 2020b)), the United States (1 km) (McKee et al. 2015, Zoraghein and O’Neill 2020), global coastal areas (1 km) (Merkens et al. 2016), and the Mediterranean coastal zone (1 km) (Reimann et al. 2018). However, due to their different input data and methods, combining these regional population datasets for global applications would induce unknown uncertainties.

As of now, the improved NCAR dataset by Gao (2020) is perhaps the best source of SSP-consistent high-resolution global population projections. For further improvements, needed are additional auxiliary data, novel downscaling models, and/or greater computational capacity. Thanks to the reducing cost of super computers and servers, what really hinders is to develop better models with hopefully the aid of additional predictive data. Existing studies have included historical population (Leyk et al. 2019), urban fraction under Representative Concentration Pathways (RCPs) (Boke-Olén et al. 2017, Chen et al. 2020a, Boke-Olén and Lehsten 2022), and other auxiliary variables (Leyk et al. 2019, Murakami and Yamagata 2019) as the predictors, involving downscaling methods like areal weighting techniques (Gao 2020), the share-of-growth model (McKee et al. 2015), and gravity-type models (Grübler et al. 2007, Jones and O’Neill 2016). Note that population often presents nonlinear relationships with the various predictive variables (Rohat 2018, Leyk et al. 2019), such as historical population distribution (Nieves et al. 2017, Reed et al. 2018). Yet, built-up land pattern remains insufficiently incorporated in the existing studies.

Here we incorporate a newly available fine-resolution future built-up land dataset to train a non-linear machine learning (ML) model, creating a new dataset of 1 km resolution global population projections under SSPs 1–5 throughout the 21st century for every ten years (the future population dataset, FPOP for short; available at www.geosimulation.cn/FPOP.html). Specifically, we take advantage of an SSP-consistent 1 km resolution global built-up land dataset for 2020–2100 by Chen et al. (2020c), which itself is not informed by FPOP distribution. Further, we adopt the random forest (RF) algorithm to better capture the nonlinear relationships between population and various predictive variables. The remainder is organized as follows: section 2 presents methodology and raw data. Section 3 validates and evaluates FPOP’s accuracy, following which we assess the spatiotemporal dynamics of future global population under SSPs 1–5 and associated heat exposure dynamics under contrasting SSP-RCP scenarios. Section 4 discusses some key findings that deserve research and policy attention.

2. Data and methodology

2.1. Population projection using machine learning

The core of our methodology is recursive projections for every ten years from 2010 to 2100 by using an ML framework (i.e. RF) to capture the potentially nonlinear relationships between a range of predictive factors and gridded population (figure 1). The exceptional accuracy of our projections, as detailed below, results from a combination of three methodological peculiarities. First, we adopted a recursive approach—a conventional practice in existing population projection studies (Chen et al. 2020a, 2020b)—to extend gridded projections at an earlier time $T_i$ onto the next time point $T_{i+10}$, i.e. ten years later. The underlying assumption is that population distribution is path-dependent, influenced by a legacy effect. Second, in addition to a few commonly
used predictive factors—i.e. slope, distance to city center, distance to roads, and distance to water, as highlighted in previous studies (Stevens et al. 2015, Nieves et al. 2017)—we further incorporated the SSP-consistent 1 km future global built-up land dataset by Chen et al. (2020c) to improve prediction (see figure S1 for a comparative illustration justifying our use of the 1 km projection by Chen et al. (2020c) instead of a 0.125 degree data by Gao and O’Neill 2020). The underlying assumption is that population distribution is closely related to built-up land.

Third, similar to the idea of Cellular Automaton, we used derived data from population and built-up land grids by applying $3 \times 3$, $5 \times 5$, and $7 \times 7$ moving windows—following Chen et al. (2020b)—to account for multi-scale neighborhood effects. The underlying assumption is Tobler’s First Law of Geography that “[e]verything is related to everything else, but near things are more related than distant things.”

For each projection, the SSP-consistent global population count and ten gridded layers (figure 1; table 1) were used as inputs of the predictive RF algorithm, which was trained and tested at the year 2010 (see supplementary material for critical methodological details). The prediction performance of the trained RF algorithm was evaluated at multi-scales against the adjusted WorldPop 2020 data (version: unconstrained individual countries 2000–2020 UN adjusted-1 km resolution) and further, compared with five existing gridded FPOP datasets that are SSP-consistent, including NCAR, CoastalZone, AFRICA, China_CAI, and China_CHEN (table 2). The accuracy assessment and comparison were based on the percent root relative squared error ($%\text{RRSE}$) (Raji and Vinod Chandra 2016, Khan et al. 2020, Kumar and Susan 2020) for comparison across scales and regions. It is calculated as follows:

$$%\text{RRSE} = \frac{\sum_{i=1}^{n} (\text{Pred}_{(i)} - \text{Act}_{(i)})^2}{\sum_{i=1}^{n} (\text{Act}_{(i)})^2} \times 100\% \quad (1)$$

where $n$ is the total number of grids, Pred$_{(i)}$ denotes the predicted population at the $i$th grid, and Act$_{(i)}$ denotes the corresponding adjusted WorldPop population in 2020, while Act$_{(i)}$ denotes the mean of Act$_{(i)}$ (i.e. the gridded adjusted WorldPop population in 2020 averaged over the total of $n$ grids). Besides, seven representative urban regions—Cairo, Egypt; Melbourne, Australia; New York, USA; Paris, France; Sao Paulo, Brazil; Tokyo, Japan; and Yangtze River Delta, China—were mapped in terms of their 2020 WorldPop populations and the corresponding projections of the five existing datasets and our study. In so doing, the projection accuracy can be visually contrasted.

2.2. Extreme heat exposure assessment

Accurate population data is critical for a wide range of sustainability issues, of which exposure to extreme heat is a typical concern. Following the method adopted by Liu et al. (2017), Jones et al. (2018) and Chen et al. (2020b), we calculated extreme heat exposure as the product of population times the yearly frequency of extreme heat days (unit: person per day), as follows:

$$E^T_{(i), \text{pop}} = P^T_{(i)} \times H^T_{(i)} \quad (2)$$

where $E^T_{(i), \text{pop}}$ and $P^T_{(i)}$ denote respectively the extreme heat exposure and population at the $i$th grid in year $T$, and $H^T_{(i)}$ denotes the yearly frequency of extreme heat days for the $i$th grid.
and $H_i^T$ is the frequency of extreme heat days at the $i$th grid during year $T$. Here, an extreme heat day is defined as one when its highest daily temperature is no less than 35 °C (see supplementary material for methodological details).

Following the scenario setting rationale in Jones et al. (2018) and Chen et al. (2020b), population dynamics under SSP3 and SSP5 were considered for estimating future extreme heat exposure; SSP3 represents a world with rapid population growth in most regions and low urbanization, while SSP5 depicts low population growth and high urbanization (see table 2 in O’Neill et al. 2017 for detail). Besides, to quantify the impact of population dynamics on extreme heat exposure, the Thiel-sen slope (Sen 1968) was calculated to measure the rate of change in extreme heat exposure for each continent (except Antarctica) from 2020 to 2100. The same method was applied to study the population dynamics from 2020 to 2100 in regions of different population densities.

### 3. Results

#### 3.1. Accuracy comparison between FPOP and existing datasets

We compared the projection accuracy of FPOP and five existing gridded population datasets, i.e. NCAR, CoastalZone, AFRICA, China_CAI, and China_CHEN (table 2). As noted in section 2.1, the %RRSE was used as the accuracy measure of the projections against the adjusted WorldPop population in 2020 for the globe, major continents and regions (see figure 2(a) for grid-accuracy’s mean and table S1 for standard deviation). FPOP has a %RRSE of 34.10% at the global scale, contrasting to 84.24% for NCAR and 139.42% for CoastalZone. The improved accuracy of our population projections also applies to the six populated continents. Our accuracy outperforms the existing datasets by up to 54% in Asia, 97% in Africa, 53% in North America, 47% in Oceania, and 47% in South America. For China, particularly, the relative accuracy improvement of our projections is up to 112%. To quantify our accuracy at the country scale in the absolute sense, we further regressed our national projections against the population counts of 227 countries in 2020 based on globally comparable data of the World Population Prospects 2019 by United Nations (2019), which shows a near-perfect $R^2$-square of 0.99 (figure 2(b)). The multi-scale accuracy assessments suggest that our data would provide the best available population projections at the global, continental, and national scales.

The accuracy improvement of FPOP as compared with the existing datasets seems to also hold across various populated metropolitan areas (figure 3). We made a visual comparison based on the spatial distribution of adjusted WorldPop and projected population densities in 2020 in seven typical metropolitan areas at the same spatial resolution of 1 km. The comparison consistently illustrates the qualitatively better accuracy of FPOP. Quantitatively, FPOP again has the lowest %RRSE for all the seven metropolitan areas as compared with the five existing datasets. For one, our %RRSE for Cairo, Egypt is 32.28%, while those of NCAR, CoastalZone, and AFRICA are 87.24%, 90.04%, and 57.31%, respectively. For another, our %RRSE for the Yangtze River Delta, China is 25.45%, while those of NCAR, CoastalZone, AFRICA, China_CAI, and China_CHEN are 88.13%, 82.22%, 71.31%, and 134.60%, respectively. The comparison for the other five metropolitan areas

### Table 1. Data used for SSP-consistent population modeling in this study.

| Dataset                                | Year     | Resolution | Source               |
|----------------------------------------|----------|------------|----------------------|
| Global Population Maps                 | 2000, 2010 | 1 km       | Lloyd et al (2019)   |
| Environmental Variables Maps           | City center Roads Water Slope | 1 km | Natural Earth |
| Historical Global Built-up Land        | 2010     | 30 m       | Liu et al (2020)     |
| Global Built-up Land Scenarios         | 2010–2010 | 1 km       | Chen et al (2020c)   |
| Global Population Scenarios            | —        | —          | Riahi et al (2017)   |

### Table 2. Existing gridded population datasets for comparison with our product.

| Scenario     | Dataset       | Scale       | Year     | Resolution | Source               |
|--------------|---------------|-------------|----------|------------|----------------------|
| SSPs         | WorldPop      | Global-scale| 2020     | 1 km       | Lloyd et al (2019)   |
| NCAR         | Geo 2010–2100 | 1 km       | Gao (2020)|            |                      |
| Coastal Zone | Geo 2005–2100 | 1 km       | Merkens et al (2016)|     |                      |
| AFRICA       | Geo 2010–2100 | 1 km       | Boke-Olén et al (2017)| |                      |
| China_CAI    | Geo 2010–2100 | 1 km       | Chen et al (2020a)   |            |
| China_CHEN   | Geo 2015–2050 | 100 m      | Chen et al (2020b)   |            |
Figure 2. (a) Accuracy comparison of existing gridded population datasets and FPOP. The accuracy was measured by %RRSE of predicted population against adjusted WorldPop population in 2020. FPOP has consistently higher grid-average accuracy. See table S1 for the standard deviation of %RRSE. (b) Validation of our population dataset in 2020 at the country scale (227 countries in total). The circle size is proportional to the ratio of population over built-up areas in a country. The subfigure at the bottom right shows the top three countries by population for better presentation. Importantly, the population count constraint on spatial allocation in FPOP is SSP-consistent global population counts instead of the conventionally-used national counts. See supplementary material for methodological details and discussion.

(i.e. Melbourne, Australia; New York, United States; Paris, France; Sao Paulo, Brazil; and Tokyo, Japan) also confirms that FPOP has quantitatively substantial accuracy improvement over the existing datasets.

3.2. Projected future population dynamics by SSP and population density

Based on the above accuracy assessment of our population projection algorithm, we then simulated future global population under SSPs 1–5 at a 1 km resolution for 2000–2100 at ten-year intervals, with the projections starting from 2010 (see section 2 for details). The projected populations in high-, medium-, low-density areas show a similar trend under all SSPs, except for SSP3 when the global population—particularly the population of high-density areas—was projected to increase all the way to 2100 (figures 4(a)–(e)). Contrarily, the trend under the other SSPs is consistent that the population would first increase until some point during the second half of the 21st century and then decrease till 2100. Relatedly, the spatial pattern of the global population is also similar, except that the populous (high- and medium-density) areas in places such as India, China, and parts of central Africa expand remarkably under SSP3 compared with the other SSPs (figures 4(A)–(E)). Generally speaking, the whole nation of India and the southeast half of China would be the most populous across the globe, followed by west and central Europe, southeast Asia, west and central Africa, and lastly, the fragmentedly-distributed built-up areas in east America and Latin America. The spatial pattern and temporal trend of the global population under SSP3 show stark contrast to those under the other four SSPs, indicating the critical need of enhancing proactive research and strategic policy interventions for an increasingly likely future where regional rivals and competitions divide the global community (i.e. SSP3)—as signaled by trade wars and travel bans in the recent years.

The trends of population change, like the trends of population per se, seem to show the strongest Matthew effect under SSP3, which is followed by SSP2 and SSP4, and lastly SSP5 and SSP1 (figure 5). To be specific, those high- and medium-density areas (e.g. India, southeast China, southeast Asia,
Figure 3. Comparison of population predictions in 2020 against the adjusted WorldPop population distributions across typical regions. The %RRSE for each metropolitan area is shown at the bottom left corner of each subfigure. Despite the 1 km resolution, other datasets have a coarser population distribution than ours. Our projections are more uniform and closer to the adjusted WorldPop population distributions.

west and central Europe, central Africa, and east America) appear to experience more drastic population growth during 2020–2100, while those low-density or population-sparse areas (e.g. southwest China, west Sub-Saharan Africa, and central America) are more inclined to have population decline (figures 5(A)–(E)). However, this qualitative observation of spatial variations is not in line with the contrast of decadal population changes by different type density areas. In most cases, actually, the decadal population change rate in each of three density areas ranks as follows: population-sparse, low-density, medium-density, high-density (figures 5(a)–(e)). In other words, the Matthew effect that densely-populated grids seem to have more population growth (or less population decline) holds only at the grid level yet not at the category level. It suggests notable variations within each population-density category, and may indicate that FPOP would become regionally polarized/centralized.

3.3. Projected dynamics of future heat exposure by SSP-RCP and continent

The SSP-consistent, spatially-explicit future global population projections make it possible to do prognostic assessments of alternative socioeconomic development and climate policies. As an example of global concern, here future global heat exposure and dynamics are estimated under different scenario settings of SSP and RCP (see section 2 for details) by combining FPOP and future daily maximum temperature projections (figure S3). Different SSP and RCP settings would remarkably affect future global heat exposure (figures 6(a)–(d)). The
Figure 4. Spatial patterns of projected global population in 2100 under SSPs 1–5 (A)–(E) and temporal trends between 2020 and 2100 under corresponding SSPs (a)–(e). The projected 2100 global population shows similar patterns under SSPs 1–5; yet the populous areas in places such as India, China, and parts of central Africa expand remarkably under SSP3 compared with other SSPs. Relatedly, the global population—particularly the population of high-density areas—was projected to increase steadily from 2020 to 2100 under SSP3, contrasting to the consistent trend under other SSPs that the population would first increase up to the second half of the 21st century and then decrease till 2100.

worst situation would occur under SSP3-RCP8.5—a future scenario featured by low urbanization, exponential population growth, and high greenhouse gas emission. Under this very scenario, the global heat exposure would increase almost exponentially, i.e. from 315 billion person-days at 2020 to over 1626 billion person-days in 2100, an increase by 416% (figure 6(c)). Under the contrary scenario, SSP5-RCP4.5, which is featured by high urbanization, slow population growth, and low emission, the global
Figure 5. Spatial patterns of projected population change from 2020 to 2100 under SSPs 1–5 (A)–(E) and the rates of change per decade under corresponding SSPs (a)–(e). Negative rates denote population decline while positive values mean population growth. The projected population change pattern is similar among the five SSP scenarios, following the Matthew effect of different degrees (SSP3 > SSP2 ≈ SSP4 > SSP5 ≈ SSP1). The decadal change rate shows that, while the global population would increase steadily under SSP3, it would increase up to 2070 and then decrease under SSP2, SSP4, and SSP5 and have the year 2050 as the tipping point under SSP1. Negative rates denote population decline while positive values mean population growth.

Heat exposure would increase by only 62% from 318 billion person-days at 2020–516 billion person-days in 2100. From a spatial perspective, the future heat exposure shows a similar global pattern under different SSP-RCPs, i.e. typical areas with high exposure are the Ganges River Basin, Indus valley, eastern China, southeast Asia, and Sub-Saharan Africa, while those with much lower exposure include South America, North America, Europe, and Oceania (figures 6(A)–(D)). In general, Asia and Africa...
Figure 6. Global patterns of projected heat extreme exposure in 2100 under SSP3-RCP4.5 (A), SSP5-RCP4.5 (B), SSP3-RCP8.5 (C), and SSP5-RCP8.5 (D), as well as temporal trends between 2020 and 2100 under corresponding scenarios (a)–(d). Results show that both SSP and RCP settings would affect the projected heat exposure, with the most dramatic exposure occurring under SSP3-RCP8.5. The contrast seems to be dominated by the different trends of exposure in Asia—it would increase almost exponentially under SSP3-RCP8.5 while contrastingly, decrease after 2080 or experience lower increase in the second half of 21st century under the other three scenarios.

account respectively for 64%–68% and 21%–25% of the global exposure, while the remaining areas together contributing to 8%–15%.

Like the patterns of population change under different SSP-RCPs, the global patterns of heat exposure change during 2020–2100 also show the Matthew effect—where is more heat-stricken is also projected to suffer from more incremental heat exposure (figures 7(A)–(D)). The least heat-stricken regions largely overlap with the global population-sparse areas, e.g. deserts in Africa, Oceania, and northwest China as well as the Arctic. From a temporal perspective, the projected exposure would increase in each region during 2020–2100 (figures 7(a), (c) and (d)), except for the last two decades of the 21st century under SSP5-RCP4.5 (figure 7(b)). Generally, the decadal increase rate of heat exposure would decrease over time during 2020–2100. Under RCP4.5, the decrease is approximately 35% in North America, 20% in Oceania, 12% in Europe and Africa, and 10% in Asia. Under RCP8.5, the decrease is about 36% in North America, 25% in Oceania, 35% in Europe, and 15%–20% in Africa and Asia. It should be noted that the exposure change rate of South America shows dramatic fluctuations after 2070 under RCP 4.5 and after 2050 under RCP 8.5. Notably, under the
Figure 7. Global patterns of projected heat exposure change from 2020 to 2100 under SSP3-RCP4.5 (A), SSP5-RCP4.5 (B), SSP3-RCP8.5 (C), and SSP5-RCP8.5 (D), as well as temporal trends between 2020 and 2100 under corresponding scenarios (a)–(d). The projected exposure change pattern is similar among the four scenarios, with the largest increase in India and China under SSP3-RCP8.5 and the largest decrease occurring in central Africa under SSP5-RCP4.5. The decadal change rate shows that overall the projected exposure would increase in each region during 2020–2100, except for the last two decades of the 21st century under SSP3-RCP8.5. Besides, the exposure in South America shows dramatic fluctuations, especially at around 2090.

4. Discussion and conclusions

The significance of long-term trends and global patterns of population dynamics has been made clear in the existing literature (e.g. public health and environmental protection (Kii 2021), floods (Tate et al 2021), droughts (Liu and Chen 2021)). In this vein, our demonstration study that applies the improved FPOP (see supplementary material for methodological discussion) to assess future global heat exposure during 2020–2100 makes at least three contributions. First, from a spatial perspective, FPOP projects a consistent global pattern of future heat exposure under SSP3-RCP4.5, SSP3-RCP8.5, SSP5-RCP4.5, and SSP5-RCP8.5 (figures 6(A)–(E)), confirming the findings by Liu et al (2017, figure 1 therein) and Jones et al (2018, figure 1 therein). Our results also depict that future increment of high exposure areas would most likely occur in the tropical and sub-tropical regions (figures 7(A)–(E)), and that the worst scenario is SSP3-RCP8.5 (figures 6(a)–(c)). Our study
additionally provides the continental shares of the global exposure, highlighting the primary contributor of Asia (64%–68%) and secondary role of Africa (21%–25%). Our study also hints on the Matthew effect of future exposure dynamics at the grid scale (figures 7(A)–(E)), which has important policy implications deserving further investigation.

Second, the contrast of global/continental exposures under different SSP-RCPs suggests that climate policies (the RCP setting regarding greenhouse gas emission) seems slightly more influential than socioeconomic policies (the SSP setting regarding population and urbanization) (figures 6(a)–(e)). Our preliminary conclusion is consistent with Jones et al (2015) in the context of the U.S. and the observation by Jones et al (2018) in their global-scale study. However, there are contradictory studies. For example, Liu et al (2017) conclude the contributions of future climate change and global population dynamics would respectively account for 28% and 9%, with the main contribution coming from their interaction (66%). Huang et al (2018) show that in the context of China the contributions of climate change and population dynamics are 60%–70% and 20%–40%, respectively. Besides, a recent historical study by Tuholske et al (2021) suggests that the impact of population dynamics on global urban population exposure to extreme heat is about two times that of warming. Despite these inconclusive findings, it seems climate policies would be relatively more effective than population policies in addressing future global heat exposure.

Last, our estimates of future global heat exposure under the various SSP-RCPs are substantially larger than those of existing findings, though consistent in terms of the magnitude. FPOP-based global heat exposure under the four SSP-RCPs is around 300 billion person-days in 2020, and by the end of the 21st century, could increase to as high as 1626 billion person-days under the four SSP-RCPs (table 52). Against the FPOP-based results, NCAR underestimates the exposure in densely-populated areas (e.g. India, southeast China, southwest Asia, west and central Europe, South Africa, east and central America) by up to 3.77%, and overestimates in sparsely-populated areas (e.g. southwest China, North and central Africa, west America) by as much as 67.42% (figure S6); CoastalZone overestimates the exposure in densely-populated areas (e.g. India, China coast, southeast Asia coast, east Europe, and east America) by as much as 52.89%, and underestimates in inland areas (e.g. central China, central America, central Europe, central southeast Asia and Sub-Saharan Africa) by as much as 89.02% (figure S7). The mis-estimation and spatial distribution due to inaccurate population projections are far from trivial. A recent study by Burkart and colleagues (Burkart et al 2021) reports that 356 000 deaths worldwide in 2019 were linked to heat extremes. The death number may seem not so alarming, yet with the projected increase by 2100 and the mis-/underestimation due to inaccurate population projections, can translate into more dramatic deaths and devastating loss for the families involved. As none of the existing datasets are perfect including FPOP, continuing efforts should be invested to keep improving gridded future global population projections and to reexamine future exposures and vulnerabilities associated with other widely-concerned hazards, such as flooding (Kirezci et al 2020), extreme cold (Batibenz et al 2020, Broadbent et al 2020), and typhoon (Yin et al 2021).

Data availability statement

Any data that support the findings of this study are included within the article (and any supplementary files). The historical global population maps are available at www.worldpop.org/. The United Nations Population can be obtained at https://population.un.org/wpp/Download/Standard/Population/. The historical global built-up land maps can be retrieved from...
https://figshare.com/articles/dataset/High_spatio
temporal_resolution_mapping_of_global_urban_cha-
enge_from_1985_to_2015/11513178/1. The official
SSP database can be obtained at https://intcat.iaias.
acat/SspDb/. The environmental variables maps are
calculated from www.naturalearthdata.com/. Theive existing gridded population data-
sets for comparing with FP0P are available from
https://sedac.ciesin.columbia.edu/data/
set/popdynamics-1-km-downscaled-pop-base-
year-projection-ssp-2000-2100-rev01 (NCAR),
https://figshare.com/s/9a94ae958d6a45684382
(Coastal Zone), https://dataguru.lu.se/doc:10.18161/
popcount.201610 (AFRICA), https://springnature.
figshare.com/collections/Provincial_and_gridded_
population_projection_for_China_under_shared_
socioeconomic_pathways_from_2010_to_2100/
4605713 (China_CAI), https://figshare.com/articles/
dataset/Mainland_China_SSP_Population_Grids/
11634372 (China_CHEN), respectively.

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Author contributions

X L and Y C conceived research and planned ana-
lysis; X L, B Z, M L, and Y C improved experiment
design; M L performed computational experiments and
statistical analysis; M G, M H, Y C, and G H
provided technical and data supports; M L and B Z
drafted manuscript; B Z, M L, X L, and Y C revised
manuscript.

Conflict of interest

The authors declare they have no actual or potential
competing financial interests.

References

Batibeni Z, Ashfaq M, Diffenbaugh N S, Key K, Evans K J,
Turuncoglu U U and Ondol B 2020 Doubling of US
population exposure to climate extremes by 2050
Earth’s Future 8 2019EF001421
Boke-Olén N, Abdin A M, Hall O and Lehsten V 2017
High-resolution African population projections from
radiative forcing and socio-economic models, 2000–2100
Sci. Data 4 1–9
Boke-Olén N and Lehsten V 2022 High-resolution global
population projections dataset developed with CMIP6 RCP
and SSP scenarios for year 2010–2100 Data in Brief
40 107804
Broadbent A M, Krayenhoff E S and Georgescu M 2020 The
motive drivers of heat and cold exposure in 21st century US
cities Proc. Natl Acad. Sci. 117 21018–17
Burkart K G et al 2021 Estimating the cause-specific relative risks
of non-optimal temperature on daily mortality: a two-part
modelling approach applied to the global burden of disease
study Lancet 398 685–97
Chen G et al 2020c Global projections of future urban land
expansion under shared socioeconomic pathways Nat.
Commun. 11 1–12
Chen Y, Guo F, Wang J, Cai W, Wang C and Wang K 2020a
Provincial and gridded population projection for China
under shared socioeconomic pathways from 2010 to 2100
Sci. Data 7 1–13
Chen Y, Li X, Huang K, Luo M and Gao M 2020b High-resolution
gridded population projections for China under the shared
socioeconomic pathways Earth’s Future 8 e2020EF001491
Coccia M 2020 An index to quantify environmental risk of
exposure to future epidemics of the COVID-19 and similar
viral agents: theory and practice Environ. Res. 191 110155
 Dahmm H 2021 Leaving no one off the map: a guide for gridded
population data for sustainable development 2020
(Thematic Research Network on Data and Statistics
(TReNDS)) (available at: https://static1.squarespace.com/
static/5b4f63e14edec374f616232/5eb2656ec5750
608adb1feb/1588770424043/Leaving-no-one-off-the-map-1.pdf)
Freire S et al 2018 Enhanced data and methods for improving
open and free global population grids: putting ‘leaving no
one behind’ into practice Int. J. Digit. Earth 13 61–77
Gao J 2020 Global 1-km Downscaled Population Base Year and
Projection Grids Based on the Shared Socioeconomic
Pathways, Revision 01 (Pulisdies, NY: NASA Socioeconomic
Data and Applications Center (SEDAC)) (https://doi.org/
10.7927/q79-9e69)
Gao J and O’Neill B C 2020 Mapping global urban land for the
21st century with data-driven simulations and shared
socioeconomic pathways Nat. Commun. 11 1–12
Grübler A, O’Neill B, Rathi K, Chirkov Y, Goujon A, Kolp P,
Prommer I, Scherbov S and Slentoe E 2007 Regional,
national, and spatially explicit scenarios of demographic and
economic change based on SRES Technol. Forecast. Soc.
Change 74 980–1029
Gu D 2019 Exposure and vulnerability to natural disasters for
world’s cities Technical Paper (United Nations Department of
Economic and Social Affairs, Population Division)
Huang D, Zhang L, Gao G and Sun S 2018 Projected changes in
population exposure to extreme heat in China under a
RCP8.5 scenario J. Geogr. Sci. 28 1371–84
Huang K, Li X, Liu X and Seto K C 2019 Projecting global urban
land expansion and heat island intensification through 2050
Environ. Res. Lett. 14 114037
Jones B and O’Neill B C 2016 Spatially explicit global population
scenarios consistent with the shared socioeconomic pathways
Environ. Res. Lett. 11 084003
Jones B, O’Neill B C, McDaniel L, McGinnis S, Mearns L O and
Tebaldi C 2015 Future population exposure to US heat
extremes Nat. Clim. Change 5 652–5
Jones B, Tebaldi C, O’Neill B C, Oleson K and Gao J 2018 Avoiding
population exposure to heat-related extremes: demographic
change vs climate change Clim. Change 146 423–37
Khan B, Naseem R, Muhammad F, Abbas G and Kim S 2020 An
empirical evaluation of machine learning techniques for
chronic kidney disease prophecy IEEE Access 8
55012–22
Kii M 2021 Projecting future populations of urban
agglomerations around the world and through the 21st
century npj Urban Sustain. 1 1–12
Kirecci E, Young I R, Ranasinghe R, Muis S, Nicholls R J, Lincke D
and Hinkel J 2020 Projections of global-scale extreme sea
levels and resulting episodic coastal flooding over the 21st
Century Sci. Rep. 10 1–12
Kriegler E, Edmonds J, Hallegratte S, Ebi K L, Kram T, Riahi K,
Winkler H and Van Vuuren D P 2014 A new scenario
framework for climate change research: the concept of
shared climate policy assumptions Clim. Change 122 401–14
Kulp S A and Strauss B H 2019 New elevation data triple
estimates of global vulnerability to sea-level rise and coastal
flooding Nat. Commun. 10 1–12
Kumar N and Susan S 2020 COVID-19 pandemic prediction using time series forecasting models 2020 11th Int. Conf. on Computing, Communication and Networking Technologies (ICCCNT) (IEEE) pp 1–7

Leyk S et al 2019 The spatial allocation of population: a review of large-scale gridded population data products and their fitness for use Earth Syst. Sci. Data 11 1385–409

Liu X et al 2020 High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015 Nat. Sustain. 3 564–70

Liu Y and Chen J 2021 Future global socioeconomic risk to droughts based on estimates of hazard, exposure, and vulnerability in a changing climate Sci. Total Environ. 751 142159

Liu Z, Anderson B, Yan K, Dong W, Liao H and Shi P 2017 Global and regional changes in exposure to extreme heat and the relative contributions of climate and population change Sci. Rep. 7 143909

Lloyd C T et al 2019 Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets Big Earth Data 3 108–39

Maury O et al 2017 From shared socio-economic pathways (SSPs) to oceanic system pathways (OSPs): building policy-relevant scenarios for global oceanic ecosystems and fisheries Glob. Environ. Change 45 203–16

McKee J J, Rose A N, Bright E A, Huynh T and Bhaduri B L 2015 Locally adaptive, spatially explicit projection of US population for 2030 and 2050 Proc. Natl Acad. Sci. 112 1344–9

Merkens J-L, Reimann L, Hinkel J and Vafeidis A T 2016 Gridded population projections for the coastal zone under the shared socioeconomic pathways Glob. Planet. Change 145 57–66

Murakami D and Yamagata Y 2019 Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling Sustainability 11 2106

Nieves J J, Stevens F R, Gaughan A E, Linard C, Sorichetta A, Hornby G, Patel N N and Tatem A J 2017 Examining the correlates and drivers of human population distributions across low- and middle-income countries J. R. Soc. Interface 14 20170401

O’Neill B C et al 2017 The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century Glob. Environ. Change 42 169–80

Rai J C and Vinod Chandra S S 2016 Craft survival prediction in liver transplantation using artificial neural network models J. Comput. Sci. 16 72–78

Reed F J, Gaughan A E, Stevens F R, Yetman G, Sorichetta A and Tatem A J 2018 Gridded population maps informed by different built settlement products Data 3 33

Reimann L, Merkens J-L and Vafeidis A T 2018 Regionalized shared socioeconomic pathways: narratives and spatial population projections for the Mediterranean coastal zone Reg. Environ. Change 18 235–45

Raihi K et al 2017 The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview Glob. Environ. Change 42 153–68

Rohat G 2018 Projecting drivers of human vulnerability under the shared socioeconomic pathways Int. J. Environ. Res. Public Health 15 554

Sen P K 1968 Estimates of the regression coefficient based on Kendall’s tau J. Am. Stat. Assoc. 63 1379–89

Stevens F R, Gaughan A E, Linard C and Tatem A J 2015 Disaggregating census data for population mapping using random forests with remotely-sensed and ancillary data PLoS One 10 e0107042

Szety K, Moallemi E A, Ashton E, Butcher M, Sprunt B and Bryan B A 2021 Co-creating local socioeconomic pathways for achieving the sustainable development goals Sustain. Sci. 16 1251–68

Tate E, Rahman M A, Emrich C T and Sampson C C 2021 Flood exposure and social vulnerability in the United States Nat. Hazards 106 435–57

Tuholske C, Caylor K, Funk C, Verdin A, Sweeney S, Grace K, Peterson P and Evans T 2021 Global urban population exposure to extreme heat Proc. Natl Acad. Sci. 118 e2024792118

United Nations 2019 World Population Prospects 2019 Online edn Rev. 1 (Department of Economic and Social Affairs, Population Division)

Van Vuuren D P et al 2017 Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm Glob. Environ. Change 42 237–50

Xu Y, Ho H C, Knudby A and He M 2021 Comparative assessment of gridded population data sets for complex topography: a study of Southwest China Popul. Environ. 42 360–78

Yao Y, Liu X, Li X, Zhang J, Liang Z, Mai K and Zhang Y 2017 Mapping fine-scale population distributions at the building level by integrating multsource geospatial big data Int. J. Geogr. Inf. Sci. 31 1220–44

Yin J, Lin N, Yang Y, Pringle W J, Tan J, Westerink J J and Yu D 2021 Hazard assessment for typhoon-induced coastal flooding and inundation in Shanghai, China J. Geophys. Res. 126 e2021JC017319

Zoraghein H and O’Neill B C 2020 US state-level projections of the spatial distribution of population consistent with shared socioeconomic pathways Sustainability 12 3374