Projecting population growth as a dynamic measure of regional urban warming

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Abstract

Urban development is characterized by drastic land use and land cover changes, rooted in urban population growth, with concomitant anthropogenic stressors contributing to global climate changes. While there is extensive literature on predicting future urban climate using biogeophysical models, the link between emergent meteorological patterns and the population dynamics remains weak. In this study, we propose an operative model for predicting regional urban warming using a population growth model based on different scaling laws. We choose the annual average air temperature as the climatic indicator and relate the historical temperature data to demographic data for 10 megapolitan areas in the United States. Linear regression analysis shows that the coefficients of determination range from 0.164 to 0.563 for the study areas, indicating a significant correlation between urban population and climate dynamics. Specifically, the Phoenix Metropolitan Area is selected as a testbed where the regression is applied for correlating the population growth and trend of urban warming. Based on the predicted population dynamics, the annual average temperature in Phoenix is projected to increase by 0.65 – 3.40 °C in the next 35 years.

Keywords: Climate change; Population model; Sustainability; Urban expansion

1. Introduction

From 1850 to 2005, the global emission of greenhouse gases (GHGs), such as carbon dioxide (CO₂) and methane, have been continuously increasing at an unprecedented rate, mainly due to anthropogenic emissions, with major contributors including fossil fuel combustion (Le Quéré et al., 2009), urbanization (Kalnay & Cai, 2003), and land use and land cover (LULC) changes (Feddema et al., 2005). For example, Le Quéré et al. (2009) demonstrated that the total CO₂ emission from urbanization and fossil fuel burning amounted to $9.9 \pm 0.9 \text{ Pg C yr}^{-1}$ in 2008. On the other hand, fossil fuel combustion, urbanization, and LULC changes contribute significantly to temperature increase in urban areas, though it is hard to separate the effects of urbanization and LULC changes on temperature increase (Kalnay & Cai, 2003). As a consequence, the global average surface temperature has increased by around 0.76 °C in this period (IPCC, 2007). The warming trend is projected to continue, e.g. Davis et al. (2010) predicted an increase of 1.3 °C of global mean temperature in 2060 as compared to the pre-industrial era, due to CO₂ emissions from fossil fuel combustion.

The population growth, concomitant with the global economic development, is an intrinsic driver of all the aforementioned contributors to climate changes (Rosa, York, & Dietz, 2004), which in turn prompts urban development via, e.g. technological innovations and reduced footprints of resource allocation per capita. In 1900, only about 40% of the total population was an urban resident in the U.S.; this percentage was over 75% in 1990 (Henderson, 2002). Urban growth and the associated infrastructure development/retrofit, inevitably, lead to adverse

environmental issues, such as the urban heat island (UHI) (Oke, 1973), air pollution (Mage et al., 1996), and human health issues (Patz, Campbell-Lendrum, Holloway, & Foley, 2005), to name a few. For example, the anthropogenic heat, generated from human metabolism, industries, buildings, vehicles, etc., is one of the main contributors to urban warming (Sailor, 2011). Sailor (2011) reported that the metabolic heat during daytime in U.S. cities is around 1 W m^{-2} . In industrial sectors, sensible heat is the main form of anthropogenic heat as generated by energy consumptions; accurate estimate of its magnitude is imperative but lacking (Sailor, 2011). Heiple and Sailor (2008) pointed out that energy consumptions inside buildings (mainly induced by the heating, ventilation and air conditioning systems) result in significant anthropogenic heat emissions. Additional contribution to the anthropogenic heat (and moisture) arises from vehicular emission as a result of fossil fuel combustion.

As a developed country, the U.S. has several cities of dense population, with more than 61% of the Nation's population distributed over 23 megapolitan areas (Nelson & Lang, 2011). Karl et al. (1988) quantified the correlation between increasing population and temperature among a network of 1219 stations in the U.S. from 1901 to 1981. The effect of urbanization on temperature has been detected even in small towns (population < 10000). Balling and Idso (1989) also demonstrated urban warming is associated with population growth based on historical temperature data in U.S. from 1920 to 1984. The trend is expected to continue with further urbanization and population concentration, which calls for a predictive demographic model (Bettencourt, Lobo, Helbing, Kühnert, & West, 2007), especially for cities, in order to devise an

operative tool for future urban climate projections.

For predicting future climate changes, the existing studies usually adopt biogeophysical models in conjunction with statistical techniques, such as the Coupled Model Inter-comparison Project (CMIP) (Oleson, 2012) with statistical or dynamical downscaling to study areas of interest. However, applications of such global models or reanalysis data products require expensive computational resources and in-depth understandings of the underlying dynamics of the integrated earth-atmosphere system. Instead, this study seeks an alternative way to circumvent these limitations for quantifying climate changes, specifically in densely populated regions. Our far-reaching goal is to develop a novel approach for predicting trends of urban warming by quantitatively linking the population-climate dynamics in metropolitans. Towards this end, we selected 10 megapolitan areas in the continental U.S. to statistically correlate the historical annual average air temperature and the population size in each region. In addition, the Phoenix Metropolitan Area (PMA) was chosen as a testbed for detailed statistical analysis. After validation against the historical record, the proposed model is applied for future population projection, upon which the future trend of urban temperature is then forecasted.

2. Methods

2.1 Urban population model

The population growth is an intrinsic measure of urbanization, which blends all the dynamic indicators associated with urban development such as infrastructure development,

LULC changes, anthropogenic emissions, etc. Define $N(t)$ as the population in a specific urban region at time t , the material resources at that time as $Y(t)$, the co-evolution of the available material resources and the sustained total population can be linked using a generic exponential function (Bettencourt et al., 2007):

$$Y(t) = Y_0 N(t)^\beta, \quad (1)$$

where Y_0 is the initial resource, and β is a parameter accounting for generic dynamic contributors in a community (a generic one, be it a human society or a biological group) development contributing to the population growth/decay. For example, a β value smaller than unity signifies the constraint of infrastructure and transportation materials/quantities in the built environment (Bettencourt et al., 2007). While the urban infrastructure, e.g. gasoline stations and length of electrical cables, is necessary in terms of urban development, its limitations of development or availability inevitably impose restrictions on continuous population increase. This is analogous to a biological community; e.g. for bees, when the food supply is ample, the available space in a beehive will ultimately set an upper limit of the bee population.

The consumption of the total material resources can be subdivided into two categories, i.e. for population maintenance and growth, respectively, which yields:

$$Y(t) = R_m N(t) + E \frac{dN}{dt}, \quad (2)$$

where R_m is the average amount of resource for individual maintenance per unit time per capita, with the subscript m denotes “model”, and E is the average amount of resource required for population growth per capita.

When $\beta = 1$, the driver of population growth is to sustain individual need (e.g., housing, employment, household electrical and water consumptions), leading to an exponential growth pattern. The exponential growth is well-known as a paradigmatic “free” growth mode for a generic biological community (e.g., grey seals (Bowen, McMillan, & Mohn, 2003)) or human societies (e.g., Kampala, Uganda (Vermeiren, Van Rompaey, Loopmans, Serwajja, & Mukwaya, 2012)), subject to no pressing external stress. Integrating Eq. (2) leads to:

$$N(t) = N_0 e^{(Y_0 - R_m)t/E}. \quad (3)$$

Note that for the exponent here, $(Y_0 - R_m)/E$ is time-independent. When $\beta > 1$, population growth is driven by wealth, information and resources creation (e.g., inventors, wages, GDP, etc.). Note that in this case, there will be an *initial capacity* $(R_m/Y_0)^{1/(\beta-1)}$. If the initial population N_0 is greater than this capacity there exists a threshold time t_c for population growth, after which population will collapse:

$$t_c = -\frac{E}{(\beta-1)R_m} \ln \left[1 - \frac{R_m}{Y_0} N^{1-\beta}(0) \right] \approx \left[\frac{E}{(\beta-1)R_m} \right] \frac{1}{N^{\beta-1}(0)}. \quad (4)$$

When $\beta < 1$, the growth curve should be sigmoidal with a *carrying capacity* $(Y_0/R_m)^{1/(1-\beta)}$, and the growth is related to optimal and efficient urban development (e.g. infrastructure and transportation materials or quantities).

For simplicity, R_m and E are assumed to be constants and independent of N , following the treatment in previous studies (Lane, Pumain, van der Leeuw, & West, 2009; West, Brown, & Enquist, 2001). Population growth during a few decades can be divided into several successive

cycles or time periods (stages) (Bettencourt et al., 2007). In a single stage, the initial capacity serves as a threshold for population growth with scaling $\beta > 1$, while the carrying capacity serves as the constraint for $\beta < 1$. Hence, we prescribe Y_0 as a constant with a fixed β value every year in a single stage. The ratio E/R_m is interpreted as the necessary average time for a human from birth to productive maturity, given by $E/R_m \approx \tau \times 20$ years (Bettencourt et al., 2007), where $\tau = 1$ year⁻¹. Re-arrange Eq. (2), we have:

$$N(t) = \left[\frac{Y_0^*}{R_m^*} + \left[N^{1-\beta}(0) - \frac{Y_0^*}{R_m^*} \right] \exp \left[-\frac{R_m^*}{E^*} (1-\beta)t \right] \right]^{\frac{1}{1-\beta}}. \quad (5)$$

2.2 Population-temperature regression

Here we use a statistical regression model to correlate the historical climate data to demographic data:

$$y = \beta_0 + \beta_1 x + \varepsilon, \quad (6)$$

where y is the response function, x is the regressor, β_0 and β_1 are the coefficients of linear regression, and ε is a random error term. In order to estimate the regression coefficients in Eq. (6), we adopted the least-squares estimation:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x, \quad (7)$$

where the circumflex denotes estimated value (estimator), and the regression coefficients in Eq. (6) are replaced by the least-squares estimators here.

3. Statistical Analysis in 10 U.S. Megapolitans

The development and retrofit of urban areas have significant impact on local and regional climatic changes (Kalnay & Cai, 2003). In order to deduce the relation between the trends of climatic change and population growth in cities, we collected data from 10 major megapolitan areas in the U.S. (Nelson & Lang, 2011). The demographic data from 1969 to 2014 were retrieved from the U.S. Department of Commerce, Bureau of Economic Analysis (BEA) (Brown & Wardwell, 1980; U.S. BEA, 2014). General geographic information, in particular, main cities, states, and the number of counties located within or overlapping the geographical boundaries of these megapolitan areas are summarized in Table 1.

Table 1. General geographic information of the 10 selected major megapolitan areas in the U.S.

Megapolitan areas	Main cities	Number of counties	State and counties inside megapolitan areas
Sun Corridor	Phoenix, Tucson	4	AZ
Cascadia	Seattle, Portland, Vancouver	24	OR, WA and Canada
Florida	Tampa, Miami, Orlando, Jacksonville	25	FL
Front Range	Albuquerque, Santa Fe, Colorado Springs, Denver	15	CO, NM
Great Lakes	Chicago, Detroit, Pittsburgh, Columbus, Cleveland, Minneapolis, St. Louis, Indianapolis	169	IL, IN, MI, MN, OH, PA, WI, Canada
Northeast	New York, Philadelphia, Washington D.C., Boston, Baltimore	165	CT, DC, DE, MA, MD, NY, NJ, PA, VA, WV, NH, RI
Northern California (CA)	Oakland, Reno, Sacramento, San Jose, San Francisco	27	CA, NV
Piedmont Atlantic	Atlanta, Birmingham, Raleigh-Durham, Charlotte	121	NC, SC, GA, AL
Southern California (CA)	Los Angeles, San Diego, Anaheim, Long Beach, Las Vegas	12	CA, NV and Mexico

Population in each megapolitan area is computed based on the demographical data collected at the county level, i.e., the total population of a megapolitan area is the sum of population from individual counties. For example, population in Great Lakes is the sum of population from 169 counties in this area (see Table 1). During the past 46 years (1969 – 2014), the population in all the 10 megapolitans has experienced continuous increases (Figure 1), except for the Great Lakes where fluctuations of population were observed around 1979 – 1986. Though not the largest megapolitan area in the U.S., the Northeast region is the most densely populated megapolitan with the largest population size as well as significant growth rate. Among these regions, Arizona’s Sun Corridor has seen the most rapid rate of urbanization with a population growth of more than 309% during the past five decades. The rate of population growth is lowest in Great Lakes and Northeast, which is partly due to the high level of urbanization preexisted in these areas prior to 1969.

Figure 1. Population growth in the selected megapolitan areas in (a) Sun Corridor, Cascadia, Northern California, Southern California, and Front Range, and (b) Texas Triangle, Florida, Great Lakes, Piedmont Atlantic, and Northeast during 1969 – 2014.

The temperature data were downloaded from the National Environmental Satellite, Data, and Information Service (NESDIS) of the National Oceanic and Atmospheric Administration (NOAA) (NOAA NESDIS, 2016). We averaged the archived near-surface (5 ± 1 ft) air temperature of all climate divisions in each megapolitan area to obtain the annual average temperature (AAT) of an individual megapolitan. All the 10 selected regions exhibit a trend of urban warming with some fluctuations (Figure 2) under the background of global climate changes accelerated in the past half century (Murray & Colle, 2011). Florida, Sun Corridor and Texas Triangle are the three warmest megapolitan areas in the U.S. during the past 46 years,

while Front Range and Great Lakes are the two coldest according to the AAT data. In addition, the synchronization of the AAT change is observed, for example, 1986 – 1992 and 1996 – 2001.

Figure 2. Same as Figure 1 but for AAT.

To quantify the correlation between the population growth and urban warming, we conducted linear regression analysis with a 95% confidence level for the selected megapolitans. The coefficient of determination R^2 is used to quantify the correlation level. It is clear from Figure 3 that the AAT is significantly correlated with population in most of these megapolitan areas. The statistical correlation is found to be most significant in Arizona's Sun Corridor, with a R^2 value of 0.563. The variance is expected as that the AAT data is obtained from the divisional level with areal averaging and embedded background changes without discriminating to detailed

188 land use land cover classification, whereas the population growth is obtained at county level.
189 Relation between AAT and population in Great Lakes during the past 46 years indicates large
190 data scatter relative to Arizona's Sun Corridor. Two megapolitan areas in California show similar
191 high R^2 values to Arizona's Sun Corridor, especially Southern California ($R^2 = 0.468$), revealing
192 similar temperature-population relation in this geographical region (Arizona and California),
193 while the correlation Great Lakes is slightly at variance with the general trend with a relatively
194 low R^2 value of 0.164.

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Figure 3. Statistical correlation between the AAT and population in the 10 megapolitan areas in the period of 1969 – 2014; scatter points are the historical observations, and red line is the linear regression.

4. Case Study in the Phoenix Metropolitan Area

4.1 The study area

In this study, we chose the Phoenix Metropolitan Area (PMA) as our testbed, partly informed by the strongest population-temperature correlation in Sun Corridor. As the largest metropolitan area in this region, the PMA is a desert metropolitan area of about 37000 km² and has been expanding for more than 60 years since 1950 (Brazel et al., 2007) (Figure 4). During this period, extensive LULC changes have taken place, converting agricultural and natural landscapes to the built environment. The urban expansion of the PMA was one of the highest among 100 largest metropolitan areas from 1980 to 2010 (Frey, 2012). Rapid urbanization in this region results in not only a population growth, but also temperature increases and a severe UHI (Hedquist & Brazel, 2014). For example, Brazel et al. (2007) reported an increase of 2 to 4 °C in mean minimum temperature of June in this region due to urbanization between 1990 and 2004.

Figure 4. Geographical location of the study area with national land cover (NLCD2011) (a) overlaid in the state of Arizona, and (b) PMA and weather stations

4.2 Correlating the urban climate change with urban population

The demographical data of the Phoenix-Mesa-Glendale Metropolitan Statistical Area

from BEA (2014) were used in this analysis. Population growth rates of the low, medium and high series (2015-2050) were retrieved from the Population Projections of the Arizona Department of Administration – Office of Employment and Population Statistics (ADOA-EPS) (2015). In addition, 7 NOAA land-based weather stations (NOAA NESDIS, 2016) were selected for the estimate of historical AAT data (1969 – 2014) (Figure 4b). Results for the correlation between the historical AAT and population data in the PMA using both the linear and exponential regression are shown in Figure 5.

Figure 5. Correlation between the AAT and population in the PMA using the (a) linear and (b) exponential regression.

The temperature-population relation is determined statistically as

$$T = 0.0723N + 20.7344, \quad (8)$$

using the linear regression, where T is the temperature in Celsius, and N is the population in 10^5 ;

and

$$T = 1.8201 \ln N + 16.8590. \quad (9)$$

using the exponential regression. Significant coefficients of statistical correlation were found between the populating and urban warming in both the linear ($R^2 = 0.735$) and exponential ($R^2 = 0.798$) regression (at the confidence level of 95%).

4.3 Simulating the historical population growth

In this section, the future population growth in the PMA is projected using the prognostic population model (see Section 2.1 for details), where various growth modes represent different underlying driving forces for population increases, including technological, socio-economic, and political drivers. Relative population growth rate of the PMA over time revealed the existence of accelerating and decelerating stages (Figure 6), similar to those of New York City (Bettencourt et al., 2007). However, due to different urbanization levels in these two regions, the successive shorter stages of super-exponential growth in New York City are not observed in the PMA. The reaccelerated process during a different period was strongly modulated by new emerging urban areas in the PMA, as shown in Table 2. To test the applicability of the proposed population model in simulating different population growth modes, we divide years 1969-2014 into seven different stages, with the key parameters listed in Table 3.

Figure 6. Historic record of population growth rate in PMA from 1969 to 2014.

Table 2. Emerging cities during different population growth stages in the PMA.

Years	Emerging cities and population growth facts
1969-1976	Available data since 1969(U.S. BEA, 2014). The recession during 1969 – 1970 resulted in a population spurt(Rex, 2000).
1977-1981	Glendale, Tempe, Mesa experienced their highest population growth rates(U.S. BEA, 2014).
1982-1990	East Valley (Mesa, Chandler, Tempe, and Gilbert) emerged around 1982(Ripley, 2011) http://www.eastvalleytribune.com/guide/article_ac67b832-fa97-11e0-b1eb-001cc4c03286.html . Peoria went through its highest population growth rate (over 300%)(U.S. BEA, 2014).
1991-2003	Chandler experienced an exponential growth (early 1990s), meanwhile Surprise and Avondale went through their highest population growth rates (over 300% and over 100%, respectively) (U.S. BEA, 2014).
2004-2011	Goodyear, Buckeye experienced the highest population growth rate (over 200% and over 600%, respectively). Surprise and Avondale continued to expand (population increased over 300% and over 100%, respectively). Population in El Mirage increased over 300%, and the increase in Queen Creek was over 500%(U.S. BEA, 2014).
2012-2014	Population growth has the same trend as that of the state of Arizona (ADOA-EPS, 2015), and this may be related to economy recovery.

Table 3. Calibrated parameters in the proposed model for different stages of population growth in PMA.

Period index	Stage	$N_0 (1 \times 10^5)$	β	Error $\leq$	R_m^*	E^*	R^2
(a)	1969 – 1973	10.134	1.211	$1.5\%N(t)_{\text{real}}$	0.50	1.00	0.992
(b)	1974 – 1979	13.020	1.300	$1.5\%N(t)_{\text{real}}$	0.50	1.00	0.985
(c)	1980 – 1985	16.122	1.282	$1.5\%N(t)_{\text{real}}$	0.50	1.00	0.989
(d)	1986 – 1990	20.133	0.853	$0.5\%N(t)_{\text{real}}$	0.50	1.00	0.999
(e)	1991 – 2003	23.192	0.848	$1.5\%N(t)_{\text{real}}$	0.50	1.00	0.998
(f)	2004 – 2011	36.373	0.877	$1.5\%N(t)_{\text{real}}$	0.50	1.00	0.995
(g)	2012 – 2014	43.310	1.129	$0.1\%N(t)_{\text{real}}$	0.50	1.00	0.999

Figure 7 illustrates the capacity of the population growth model in predicting population in different temporal periods as well as growth modes. Note that a superlinear ($\beta > 1$) relation is found for four periods (Figure 7a-c&g) in the PMA, suggesting the information and resources creation, such as patents and financial services, as the main driving force during these periods. Taking innovation for example, metropolitan areas are often more appealing to inventors and industries (Batty, 2008; Feldman & Audretsch, 1999). The larger β value found in the PMA suggests rapid population growth rate associated with strong driving force in the area during the above superlinear growing periods.

Figure 7. Comparison between predicted and observed historical population in the PMA; numbering of subplots follows the index in Table 3.

4.4 Projecting the future population growth

Assuming the current trend of population growth in PMA continues, and based on the calibrated parameters of the last stage (2012 – 2014), we predict the future population in the PMA up to 2050, with results shown in Figure 8. Here we denote the two theoretical population models derived from Bettencourt et al. (2007) as: (a) the *free growth model* based on Eq. (5) with $\beta = 1.0$, and (b) the *scaling model* with $\beta > 1$ or $\beta < 1$ for super-exponential or sub-exponential growth respectively, each constrained by a different set of socioeconomic conditions. In addition to the theoretical predictions, the low, medium, and high series population growth rates projected empirically by the ADOA-EPS (2015) are also presented in Figure 8. A more rapid rate of population increase predicted by the scaling model ($\beta = 1.129$) is observed as compared to that of the free growth model ($\beta = 1.0$). Meanwhile, both theoretical models predict larger population sizes than the empirical ADOA-EPS population projections in 2050. At the end of 2050, using the medium series of ADOA-EPS projection as the reference, the deviation of the population estimated by the scaling model from the reference is 24.29%, while the discrepancy of the free growth model is 13.74%. This discrepancy apparently suggests that the uncertainty of the theoretical predictions of future population becomes larger as expected, where a local stationarity is assumed in the population growth pattern and extended for a long period of time (in this case 35 years from 2016 to 2050).

Figure 8. Projected future population in the PMA based on calibrated parameters in the most recent period of 2012 – 2014.

Both the free growth and the scaling models can predict the population size in the first 15 years (2016 - 2030) with reasonable accuracy when compared against projection of the medium series, with an error less than 1%. The theoretical models underestimate population size from 2015 to 2025, but with slight overestimates from 2025 to 2030. A more significant deviation is observed between predicted and projected population from 2030 to 2050, indicating that key parameters for the theoretical population model should be updated periodically to represent dynamic population growth mode in a city, especially for regions with rapidly varying socioeconomic conditions (e.g. technology hubs).

4.5 Predicting future urban warming

The population-temperature correlation provides a simple means to forecast future urban temperature if a feasible population growth model is given, where both the linear regression (hereafter referred to as LR) in Eq. (8) and the exponential regression (hereafter ER) in Eq. (9) are used in subsequent analysis. The predicted temperature trends in the PMA using the population projections estimated from the free growth and scaling models, together with that from the medium series projection by ADOA-EPS, are shown in Figure 9, based on LR and ER population-temperature correlations respectively. It is clear that predicted future temperatures using LR are higher than those using ER, due to the superlinear characteristic of ER (i.e., the temperature increase rate slows down when population size is large, c.f. Figure 5b). All projections of temperature increase are summarized in Table 4. The scaling model with LR predicts the strongest warming from 24.1 °C to 27.5 °C over the next 35 years, while the low series population growth with ER yields the weakest warming from 23.8 °C to 24.5 °C. In 2050, the predicted temperature increase using LR relative to the reference temperature in 2016 ranges from 1.44 °C to 3.40 °C, while the increase using ER varies from 0.65 °C to 1.27 °C for different population growths.

Figure 9. Predicted trends of future temperature changes in PMA using different population projections.

Table 4. Summary of predicted temperature increase (in °C) from the reference in 2016.

Year	Linear regression (LR)					Exponential regression (ER)				
	SM	FG	HS	MS	LS	SM	FG	HS	MS	LS
2016	–	–	–	–	–	–	–	–	–	–
2020	0.25	0.25	0.32	0.27	0.21	0.13	0.13	0.17	0.14	0.11
2025	0.60	0.59	0.73	0.59	0.46	0.30	0.29	0.35	0.30	0.23
2030	1.01	0.96	1.13	0.91	0.70	0.48	0.46	0.52	0.44	0.34
2035	1.47	1.36	1.54	1.23	0.92	0.66	0.62	0.68	0.57	0.44
2040	2.02	1.80	1.94	1.52	1.11	0.86	0.78	0.82	0.68	0.52
2045	2.65	2.29	2.33	1.80	1.29	1.06	0.94	0.95	0.78	0.59
2050	3.40	2.82	2.71	2.06	1.44	1.27	1.11	1.07	0.87	0.65

* SM: Scaling model; FG: Free growth model; HS: High series; MS: Medium series; LS: Low series

In addition, we found that with LR relation, the predicted temperature increase by the scaling model of population growth is close to that by the free growth model in the period 2016 – 2035, with a difference of only 0.1 °C. Differences of the same magnitude are also observed with ER projections from 2016 to 2050. Despite the difference in population growth modes (free versus super- or sub-exponential), the predicted temperature in 2050 using the theoretical population models is higher than that based on the empirical ADOA-EPS population projections, as the latter takes into more socioeconomic constraints. Though the future PMA temperature increase predicted by the ADOA-EPS is lower, considerable discrepancies still exist between different series (vary from 0.42 °C to 1.27 °C), indicating uncertain warming effects with different population growth modes. Note that the warming range results from assumed different total fertility rates of all race groups in 2100 (ADOA-EPS, 2015), viz., ADOA-EPS projects total fertility rates will converge to 1.4, 1.9, and 2.4 for low, medium, and high series in 2100, respectively.

5. Concluding Remarks

This study proposed a novel method for predicting urban climate changes in terms of the environmental temperature based on the population dynamics, without resorting to complex climate models. Data from 10 major megapolitan areas in U.S. are analyzed for the period from 1969 to 2014. Reasonable coefficients of determination ranging from 0.164 (Great Lakes) to 0.563 (Arizona Sun Corridor) suggest that correlation between AAT and population is

statistically significant in the selected megapolitan areas. Specifically, the PMA with strong population-warming correlation was used as our testbed, and both linear and exponential regressions are tested with historical as well as projected temperature and population dataset. The proposed population growth models were validated using the historical demographic data from 1969 to 2014 in the study area. Furthermore, the predicted future population growth from 2016-2050 using the proposed model is found in reasonable agreement with the estimates from the ADOA-EPS for the first 15 years, with higher model uncertainty manifested in longterm projections.

Large discrepancies and higher uncertainty in longterm population projections indicate that periodical update of key model parameters is required for using urban population as a dynamic measure of regional climate change. This is necessary due to the fact that the urban development and/or redevelopment in individual metropolitan areas over a long period inevitably involve different modes and socio-economic drivers of population growth. In addition, with richer sets of demographic, socio-economic, and climatic data products and refined spatio-temporal analysis, the accuracy of the operative model proposed in this study is expect to be enhanced in predicting future urban climate. Comparisons against temperature outputs from climate models, especially those downscaled from global and regional reanalysis dataset or general circulation models, can further evaluate the performance of the proposed model, but hitherto remain as an open challenge. Overall, the proposed model provides a new perspective for urban climate research, and is expected to be informative to environmental sustainability

368 studies in general.

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