Associations Between Gender Gaps in Life Expectancy, Air Pollution, and Urbanization: A Global Assessment With Bayesian Spatiotemporal Modeling

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Objectives: It's evident that women have a longer life expectancy than men. This study investigates the spatiotemporal trends of gender gaps in life expectancy (GGLE). It demonstrates the spatiotemporal difference of the influence factors of population-weighted air pollution (pwPM$_{2.5}$) and urbanization on GGLE.

Methods: Panel data on GGLE and influencing factors from 134 countries from 1960 to 2018 are collected. The Bayesian spatiotemporal model is performed.

Results: The results show an obvious spatial heterogeneity worldwide with a continuously increasing trend of GGLE. Bayesian spatiotemporal regression reveals a significant positive relationship between pwPM$_{2.5}$, urbanization, and GGLE with the spatial random effects. Further, the regression coefficients present obvious geographic disparities across space worldwide.

Conclusion: In sum, social-economic development and air quality improvement should be considered comprehensively in global policy to make a fair chance for both genders to maximize their health gains.

Keywords: air pollution, spatial heterogeneity analysis, urbanization, gender gaps in life expectancy, Bayesian spatiotemporal modeling

INTRODUCTION

The gender differential in longevity has been a subject of interest for scientists. Generally, women have had longer life expectancy (LE) than men, though LE has steadily increased in both sexes during the last decades [1, 2]. Notably, the gap in gender-specific life expectancy (GGLE) is defined as the difference between LE of women and men, which has varied across space and time. For example, the GGLE were 6.9, 3.5, and 2.5 years in more developed, less developed, and least developed countries,

Abbreviations: BYM, Besag-York-Mollié model; DIC, Deviance information criterion; GGLE, Gender gaps in life expectancy; INLA, Integrated nested Laplace approximation; LE, Life expectancy; OECD, Organization for Economic Co-operation and Development; pwPM$_{2.5}$, Population-weighted concentration of fine inhalable particles; VIF, Variance inflation factors; WAIC, Watanabe-Akaike information criterion; WHO, World Health Organization.

respectively [3]. In addition, the female advantage in LE tends to be smaller among developing nations [4]. Meanwhile, the GGLE shows a difference across time. GGLE grew rapidly during most of the 20th century. Then, this trend was reversed, and the GGLE has declined since the 1980s. Prior papers found that physical health dimensions that cause morbidity and mortality are related to GGLE [5–8]. Furthermore, previous studies also indicated that income inequality and education level influence the GGLE [9, 10]. Accordingly, these facts mentioned above urge us not only to consider the gender gap in life expectancy but also to focus on the influencing factors of this spatial inequality.

Nevertheless, two knowledge gaps should be noted. First, the spatiotemporal trends of GGLE and the regional differences with the geospatial feature are largely unexplored at the global scale. Second, few studies have been performed to comprehensively investigate the environmental and social factors of GGLE and their spatiotemporal difference. For example, fine particulate matter ($PM_{2.5}$), a major component of air pollution, is ranked in the top ten leading global risk factors for disease burdens [11]. Extensive studies have revealed that long-term exposure to $PM_{2.5}$ is closely related to a reduction of LE at the country level [12–15] and cross-country level [16, 17]. Furthermore, urbanization plays a significant positive role in LE improvement [18]. A study in the U.S. also demonstrated that residents in metropolitan areas had larger gains in LE than those in non-metropolitan areas, which contributed to the widening gap [19]. Conversely, it has been found that urbanization may be an incubator for new epidemics and even pandemics that threaten human health worldwide [20, 21].

Accordingly, it is important to understand the spatiotemporal trends of GGLE and its environmental and social factors. Fortunately, Bayesian spatiotemporal modeling is a powerful tool for filling the gaps mentioned above by providing spatiotemporal patterns and producing smoothed maps to identify spatiotemporal trends and factors of public health levels [22]. Therefore, our current work examines the spatiotemporal patterns and variations of GGLE and its associations to $PM_{2.5}$ pollution and urbanization from a global perspective with the potential effect of geographic space. Data on GGLE and influencing factors are collected from 134 countries from 1960 to 2018. The Bayesian spatiotemporal and Bayesian regression models are applied. Hence, our study could provide a new perspective on a spatiotemporal basis different from the traditional study. This paper could thus be expected to offer regional-specific implications for public health policymaking.

METHODS

Variables

Life expectancy refers to the mean years of life remaining at a given age through the mortality rates observed at a given year [23]. This study considers the gap in gender-specific life expectancy (GGLE) as the dependent variable. Specifically, the value of GGLE is calculated as each country's female life expectancy minus its male life expectancy (**Table 1**).

We calculate the population-weighted $PM_{2.5}$ (**Table 1**) at the country level as a proxy variable to quantify the magnitude of air pollution in the exposed population on the country scale by using the following formula:

$$pwPM_{2.5} = \sum_{i=1}^{n} \left(PM_{2.5}^{i} \times \frac{pop_i}{pop} \right) \qquad (1)$$

In Eq. **1**, $pwPM_{2.5}$ represents the population-weighted $PM_{2.5}$ for a country; $PM_{2.5}^{i}$ refers to the value of ground-level $PM_{2.5}$ in the ith grid. pop_i is the population count in the ith grid; pop is the total population at country level. The annual concentrations of ground-level $PM_{2.5}$ in the dataset are based on simulated aerosol optical depth [24].

The urbanization rate was found to be closely positively related to LE based on previous studies [25, 26]. Therefore, the urbanization rate is selected as one of the core independent variables in this study.

Several covariates were selected in our model, including poverty level, education level, nutrition level, and the death rate from smoking, which showed significant relations to LE based on existing studies. Poverty plays an important role in LE determinants [27, 28]. In this study, the poverty gap index was collected to reflect the level of poverty, which refers to the mean shortfall of consumption/income from the poverty line. Education level, especially for female education conditions, is an important factor in the LE [29, 30]. In this paper, we collected primary education level as the indicator to measure the education level, which refers to the female pupils as a percentage of total pupils at the primary level, including enrollments in public and private schools. Daily caloric supply refers to the average *per capita* caloric availability. This indicator indicates the caloric availability delivered to households but does not necessarily indicate the number of calories consumed. A prior study showed that food calories could increase LE [31]. The death rate from smoking (both sex and age-standardized) refers to the annual deaths attributed to smoking (per 100,000 people). Previous papers indicated the negative effects of smoking on LE [32–34].

Data Sources

In this study, the data on life expectancy for females and males in each country from 1960 to 2018 are obtained from the World Development Indicators (WDIs) database published by the World Bank [35]. Further, the annual concentrations of ground-level $PM_{2.5}$ (with dust and sea salt removed) data for 1998–2016 are collected from the Global Annual $PM_{2.5}$ Grids data with the spatial resolution of 0.01°×0.01° released by EARTHDATA (https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod). We obtained the gridded population of the world at 1,000 m spatial resolution for the year 2005, according to the Socioeconomic Data and Applications Center of NASA (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4). Data on the share of urban population (% of the total population) is from the World Urbanization Prospects: 2018 Revision released by the United Nations Population Division. The data of the

TABLE 1 | Basic descriptions of the used variables (Worldwide, 1960 – 2018).

No.	Explanatory variables	Abbreviations	Unit
Y	Gender gaps in life expectancy at birth	GGLE	year
Y	Life expectancy at birth of male	LEm	year
Y	Life expectancy at birth of female	LEf	year
X_1	Population-weighted $PM_{2.5}$	pwPM$_{2.5}$	µg/m^3
X_2	Urbanization population rate	urbanpop	% of total population
X_3	Poverty gap index	poverty	-
X_4	Primary education (% female)	education	% female
X_5	Supply of calories	calories supply	kcal/capita/day
X_6	Death rate from smoking	smoking	Annual number of deaths attributed to smoking per 100,000 people

poverty gap index is from the Poverty and Inequality Platform by the World Bank, which is based on primary household survey data (https://data.worldbank.org/indicator). Data on the death rate from smoking (both sex with age-standardized) is from the Global Burden of Disease Collaborative Network by the Institute for Health Metrics and Evaluation (IHME) (http://ghdx.healthdata.org/gbd-results-tool). Data on daily caloric supply is from the Our World in Data (OWID) based on UN FAO & historical sources (https://ourworldindata.org/calorie-supply-sources). Data on education are collected from the database of the UNESCO Institute for Statistics (http://uis.unesco.org/).

Statistical Analysis

To model GGLE, a series of Bayesian spatiotemporal models are proposed (**Supplementary Table S1**), where for each country (i = 1, 2, ..., 134) and year step (t = 1960,1961, ..., 2018), the GGLE, y_{it}, was modeled by $y_{it} \sim Normal\ (\mu_{it}, \sigma_e^2)$. Here, μ_{it} denotes the expected value of y_{it} and σ_e^2 measures the variance of y_{it}. The μ_{it} could be calculated as the following formula (model M0s):

$$\mu_{it} = \alpha + s_i + \theta_t + \delta_{it} \qquad (2)$$

In Eq. **2**, α is an intercept that measures the overall y_{it} during the study period (1960–2018); The spatial term s_i, denotes the spatial random effect capturing the spatial dependency of y_{it}. We note that s_i captures the overall spatial random effects common from 1960 to 2018, describes the difference between y_{it} in the i-th country or region relative to the global average level, α. When $s_i > 0$, it indicates that the y_{it} in country i is higher than overall y_{it} across the whole study period. The term θ_t denotes a dynamic temporal trend that captures the overall temporal trend common to all countries. The δ_{it} is a space-time interaction random effect, representing a vector that varies through space and time [36]. The term δ_{it} allows spatial pattern changes from one time frame to another and temporal trend varies from one country to another.

Furthermore, a Bayesian spatiotemporal ecological regression was developed to investigate the impacts of air pollution and urbanization on GGLE and gender-specific life expectancy while adjusting for confounding factors and spatiotemporal variation. As an extension of model M0s, the variables of PM and UP (two interested variables) were considered, adjusting for confounding factors like poverty (P), education (E), calorie supply (C), and smoking (S). The new model was defined as the following formula (model M1s):

$$y_{it} = \alpha + s_i + \theta_t + \delta_{it} + \beta_1 ln\,\text{PM}_{it} + \beta_2 ln\,\text{UP}_{it} + \beta_3 ln\,\text{P}_{it} + \beta_4 ln\,\text{E}_{it}$$
$$+ \beta_5 ln\,\text{C}_{it} + \beta_6 ln\,\text{S}_{it}$$

$$(3)$$

In Eq. **3**, β_1, β_2, ..., β_6 refer to the corresponding regression coefficients of pwPM$_{2.5}$, urbanization, poverty, education, supply of calories, and smoking, respectively, measuring the effects of these six variables across 134 overall countries on y (GGLE, LEm, and LEf). A previous study found that the effects of air pollution and urbanization on LE and gender-specific LE may be spatially varied [37]. Model M1s is modified to allow each region to present its own regression coefficient to examine the spatially varied impacts of pwPM$_{2.5}$ and urbanization on GGLE and gender-specific LE. In this paper, a total of 134 countries are divided into six regions based on the definition of the World Health Organization (WHO) (i.e., Africa, Americas, Eastern Mediterranean, Europe, South-East Asia, and Western Pacific), to investigate the region-specific effects of pwPM$_{2.5}$ and urbanization on GGLE and gender-specific life expectancy, the modified regression model is shown as follow (model M2s):
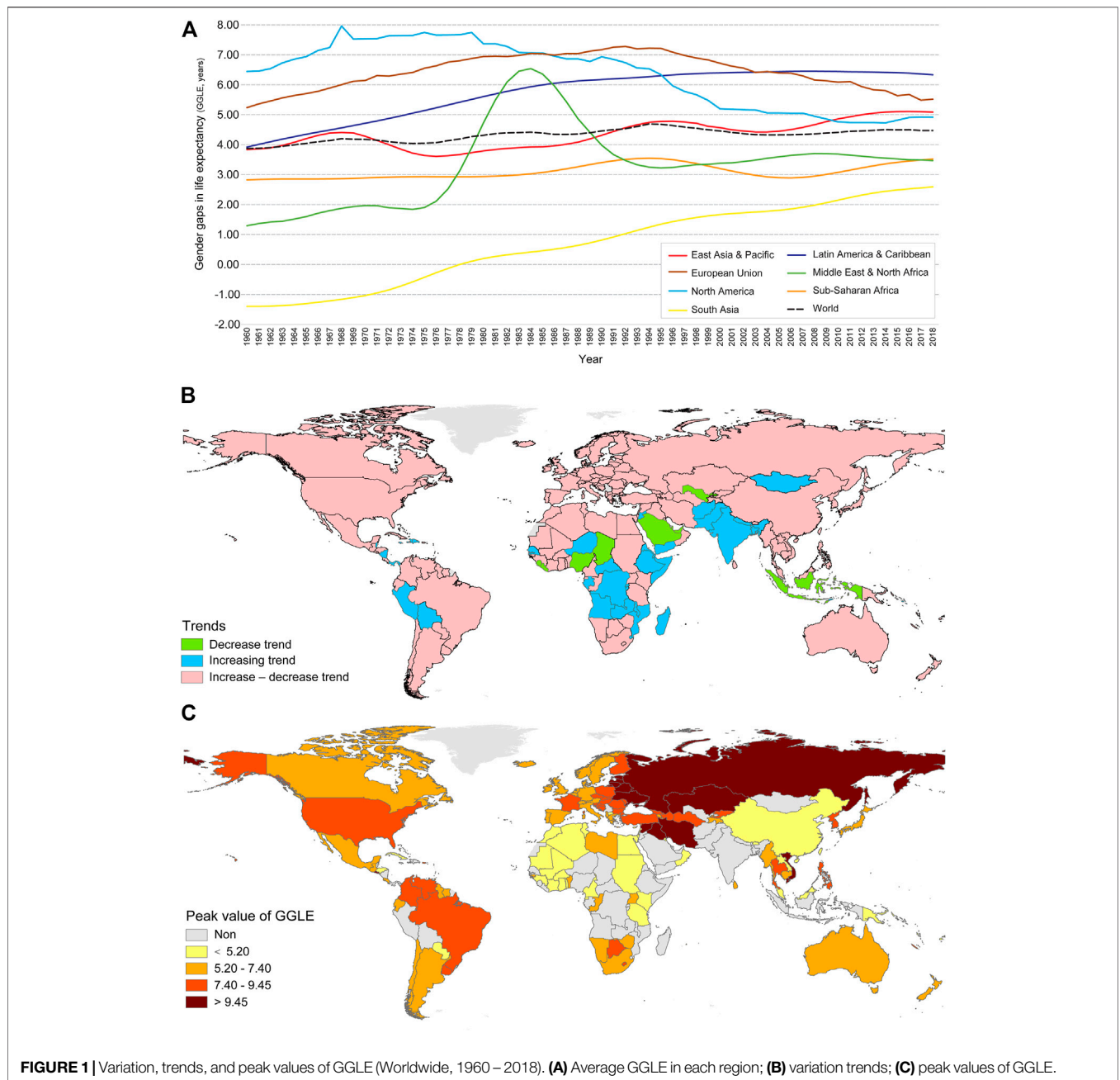
$$y_{it} = \alpha + s_i\,\theta_t + \delta_{it} + \sum\nolimits_{j=1}^{n}\beta_{1j}ln\,\text{PM}_{it} + \sum\nolimits_{j=1}^{n}\beta_{2j}ln\text{UP}_{it}$$
$$+ \beta_3 ln\,\text{P}_{it} + \beta_4 ln\,\text{E}_{it} + \beta_5 ln\,\text{C}_{it} + \beta_6 ln\,\text{S}_{it} \qquad (4)$$

In Eq. **4**, β_{1j} and β_{2j} represent the regression coefficients of influencing factors in a different region, j = 1, 2, . . ., n (n = 6). For detailed methods, please refer to the supplementary materials.

RESULTS

Distribution and Variation Trends

The average GGLE at the country level and the world is illustrated from 1960 to 2018 (**Figure 1**). Some key points can be drawn. Firstly, we could find the spatial difference across regions. Europe and North American countries show the highest peak values of GGLE, which shows a trend of rising first and then falling in GGLE. Secondly, other regions show an increasing trend during the study period, similar to the global trend. Furthermore, GGLE in South Asia (e.g., India) shows an increasing trend from negative to positive values, whereas other countries show positive values of GGLE during the study period. In addition, the GGLE in the Middle East and North Africa presents an

FIGURE 1 | Variation, trends, and peak values of GGLE (Worldwide, 1960 – 2018). **(A)** Average GGLE in each region; **(B)** variation trends; **(C)** peak values of GGLE.
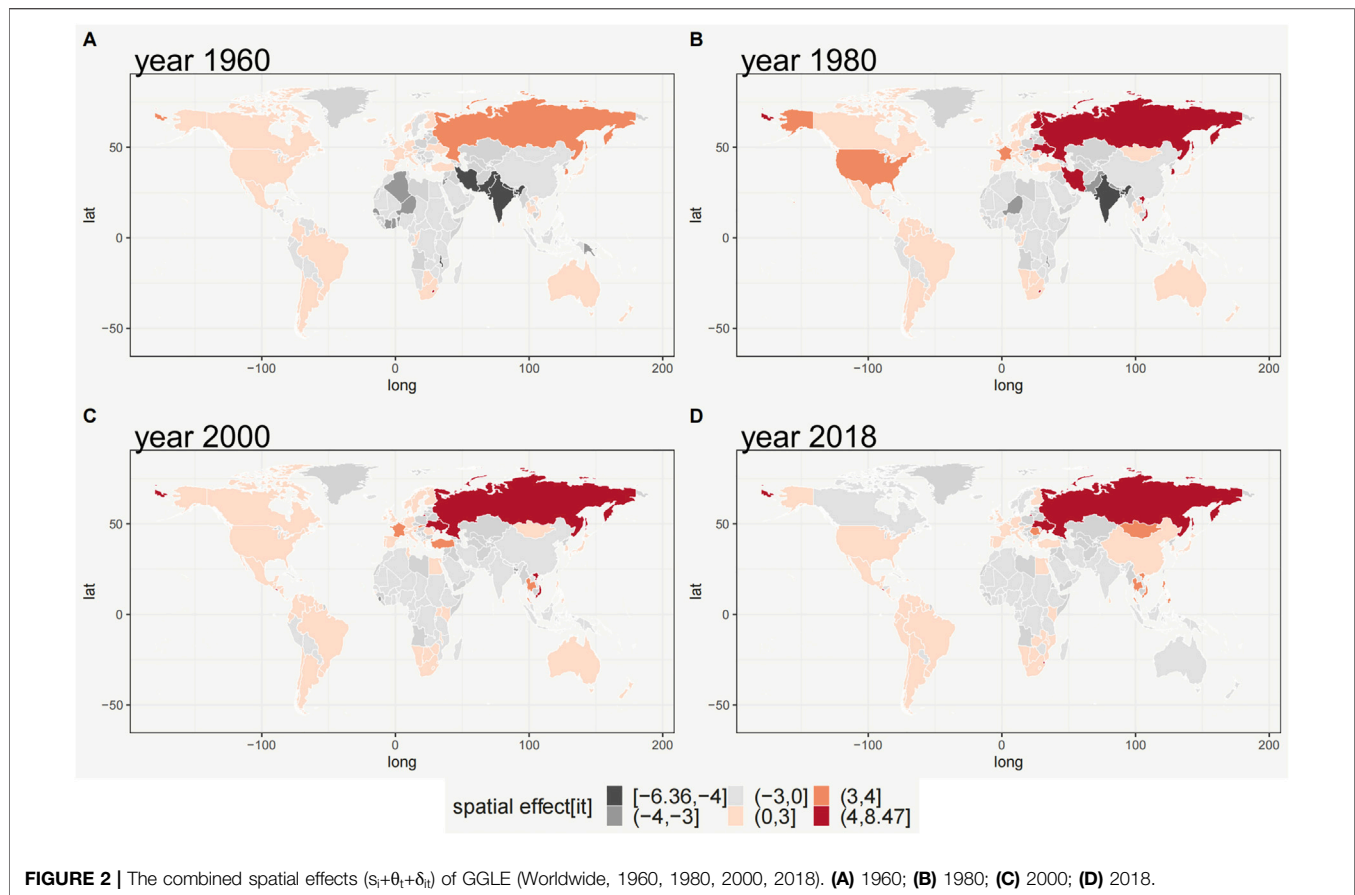
anomaly peak during the 1980s, possibly related to the sharp decreased male LE values in Iran and Iraq.

Further, most countries show a trend from increase to decrease of GGLE with peak values, 41 countries have an increasing trend without a peak value, and only 12 countries/regions show a decreasing trend without a peak value during the study period. The difference is depicted in space, indicating that the countries with increasing or decreasing trends are mainly concentrated in South Asia, Middle Africa, the Middle East, and Latin America (**Figure 1**). Countries with peak values also present spatial differences. For example, Russia and countries in East Europe,

Central Asia, Middle East show the higher level of peak values of GGLE, and countries in Western Europe, America, South Africa, Japan, South Korea, Australia, and New Zealand show the middle range of peak values of GGLE, while countries in North Africa, East-southeastern Asia show the lower peak values of GGLE (**Figure 1**).

Spatial Pattern and Its Changes Over Time

The combined spatial effects of $s_i + \theta_t + \delta_{it}$ at four different time points (1960, 1980, 2000, and 2018) for GGLE were estimated using the Bayesian spatiotemporal modeling, which depicts a

FIGURE 2 | The combined spatial effects ($s_i+\theta_t+\delta_{it}$) of GGLE (Worldwide, 1960, 1980, 2000, 2018). **(A)** 1960; **(B)** 1980; **(C)** 2000; **(D)** 2018.

spatial pattern and its changes during the study period 1960–2018 (**Figure 2**). Positive values of the combined spatial effects indicate that GGLE in country i at time point t is higher than the overall level, while negative values indicate that lower than the overall level. We found that the spatial pattern of GGLE slightly changed from 1960 to 2018. However, the whole spatial pattern is similar at these four-time points. For example, GGLE in Russia is consistently higher than the overall level. In contrast, most countries in Africa have lower GGLE than the overall level. China has a substantial change in GGLE from 1960 to 2018, which indicates a lower level in 1960, 1980, and 2000, but higher levels in 2018 compared to the overall level in the world. Other countries like the U.S., Japan, South Korea, Brazil, Argentina, and South Africa show that GGLE is consistently higher than the overall level.
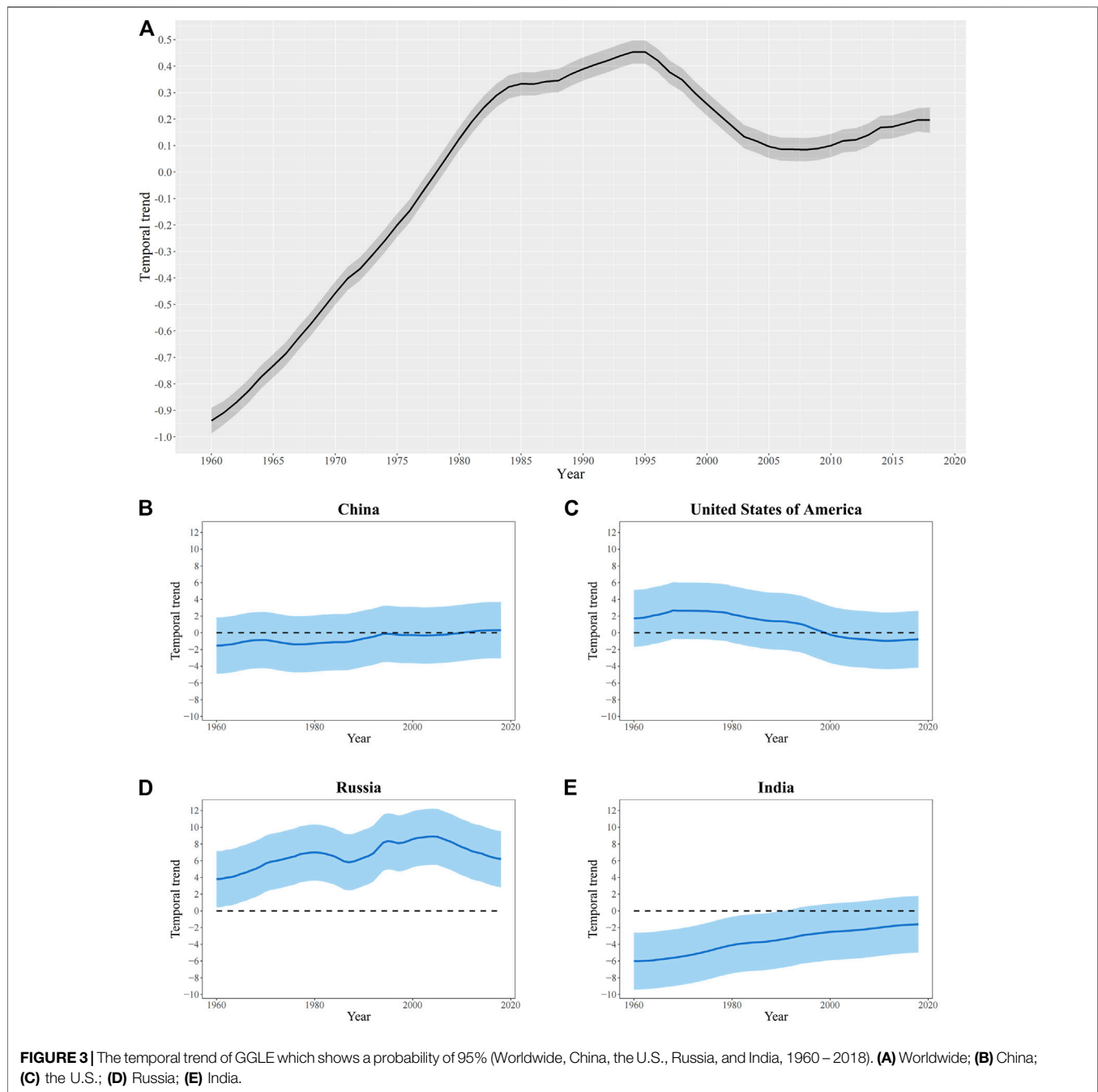
Overall and Local Temporal Trends

The overall temporal trend of GGLE (θ_t) is estimated using the Bayesian spatiotemporal model from 1960 to 2018. The overall temporal trend of GGLE presents a clear nonlinear temporal trend in the world (**Figure 3**). The GGLE increased rapidly from 1960 to 1985, and then grew slowly down but maintained an increasing trend. From 1995 to 2005, the GGLE decreased rapidly by a clear linear temporal trend. After 2005, the GGLE increased again. Moreover, we estimated the country-specific temporal trends ($\theta_t + \delta_{it}$) of GGLE to explore whether there are huge

differences across countries worldwide. **Figure 3** shows temporal trends of GGLE in four selected countries from 1960 to 2018, including China, the U.S., Russia, and India. China slightly increases GGLE, while GGLE in the U.S. shows a nonlinear temporal trend. However, there are no clear significant temporal trends of GGLE in China and the U.S. during the study period. **Figure 3** indicates that GGLE in Russia has a stronger upward trend from 1960 to 2005 but a clear downward trend from 2005 to 2018. India shows a significant increase in temporal trend. Our findings demonstrate apparent spatial differences in the local temporal trends across countries worldwide.

Influence of Air Pollution and Urbanization Factors

The global (**Table 2**) effects of air pollution and urbanization are investigated based on Bayesian regression modeling. The estimate of parameter φ suggested that the spatially structured component explained 7.7% of the variance in the overall spatial effects of GGLE (**Table 2**). However, the smaller DIC and WAIC scores derived from models with spatial random effects (**Table 2**) indicated that the spatial structure considered in the Bayesian spatiotemporal regression models could improve the data fitness. Several key findings could be observed. First, a significant positive relationship can be seen between pwPM$_{2.5}$

FIGURE 3 | The temporal trend of GGLE which shows a probability of 95% (Worldwide, China, the U.S., Russia, and India, 1960 – 2018). **(A)** Worldwide; **(B)** China; **(C)** the U.S.; **(D)** Russia; **(E)** India.

and GGLE, and no significant relations are found between $pwPM_{2.5}$ and LE in males, and females can be found. Therefore, considering spatial random effects on the global model, the GGLE increased by 0.00034% when a one percent increase in $pwPM_{2.5}$. Second, urbanization shows a significant positive relation to GGLE with spatial random effects, and significant positive relations are found between urbanization and LE in males and females as well (**Table 2**). Third, significant negative relations between poverty and GGLE can be found, while significant positive relations between calories supply, smoking, and GGLE can be identified.

Further, the six WHO regions exhibit geographic disparities in the effects of $pwPM_{2.5}$ and urbanization on GGLE and gender-specific life expectancy (**Table 3**). First, our results indicate that the negative effect of $pwPM_{2.5}$ on GGLE can be found in Africa, Eastern Mediterranean, and South-East Asia. A positive effect of $pwPM_{2.5}$ on GGLE is significant in America, Europe, and Western Pacific. No significant relations between $pwPM_{2.5}$ and LE in males and females are found in the six regions. Second, our results indicate that the negative effect of urbanization on GGLE can be found in Africa and Europe. In contrast, the positive effect of urbanization on GGLE is significant in America and Eastern Mediterranean. Significant

TABLE 2 | Global regression parameters of GGLE/male/female life expectancy, air pollution, urbanization, and control variables, estimated by posterior means of the Bayesian regression model with 95% credible intervals (Worldwide, 1960 – 2018).

	GGLE	LEm	LEf
Fixed effects			
(Intercept)	−3.026 (−4.119, −1.932)	1.979 (1.714, 2.244)	1.839 (1.574, 2.104)
pwPM2.5	0.034* (0.019, 0.048)	−0.003 (−0.007, 0.001)	−0.001 (−0.004, 0.003)
Urbanpop	0.251* (0.174, 0.328)	0.147* (0.128, 0.165)	0.153* (0.134, 0.172)
Poverty	−0.012* (−0.019, −0.005)	0.006* (0.004, 0.007)	0.005* (0.003, 0.007)
Education	−0.061 (−0.267, 0.146)	0.324* (0.274, 0.374)	0.308* (0.258, 0.358)
Calories supply	0.419* (0.304, 0.533)	0.083* (0.055, 0.111)	0.109* (0.082, 0.137)
Smoking	0.076* (0.024, 0.127)	−0.065* (−0.078, −0.053)	−0.057* (−0.070, −0.044)
Random effects (hyperparameters)			
τ_e (Precision of Gaussian error)	156 (127.62, 191)	2,530 (1910.37, 3,210)	2,860 (2,280, 3,550)
τ_s (marginal precision of BYM2)	5.11 (4.22, 6.14)	76.0 (58.4, 98.0)	79.4 (56.7, 109.0)
φ (mixing parameter of BYM2)	0.473 (0.372, 0.572)	0.665 (0.540, 0.769)	0.648 (0.456, 0.801)
τ_θ (precision of θ_t)	20,400 (7,163.735, 47,400)	60,400 (29,610.45, 110,000)	65,400 (30,500, 121,000)
τ_δ (precision of space-time interaction)	180 (142.163, 222)	3,330 (2,398.57, 4,670)	28,500 (22,800, 35,400)
Goodness of fit			
DIC	−4,433.95	−11,608.70	−11,726.27
WAIC	−4,307.81	−11,521.02	−11,698.52

TABLE 3 | Local regression parameters of GGLE/male/female life expectancy, air pollution, and urbanization estimated by posterior means of the Bayesian regression model with spatial random effects with 95% credible intervals (Six WHO regions, 1960 – 2018).

Region	pwPM2.5			Urbanization		
	GGLE	LEm	LEf	GGLE	LEm	LEf
Africa	−0.036* (−0.066, −0.007)	0.003 (−0.006, 0.012)	0.005 (−0.008, 0.018)	−0.047* (−0.079, −0.017)	0.245* (0.213, 0.275)	0.164* (0.132, 0.197)
America	0.041* (0.014, 0.067)	−0.002 (−0.006, 0.002)	−0.001 (−0.005, 0.004)	0.054* (0.026, 0.082)	0.131* (0.103, 0.158)	0.156* (0.137, 0.176)
Eastern Mediterranean	−0.297* (−0.382, −0.214)	−0.002 (−0.013, 0.007)	−0.007 (−0.024, 0.011)	0.070* (0.025, 0.120)	0.098* (0.053, 0.140)	0.139* (0.113, 0.165)
Europe	0.198* (0.152, 0.244)	0.003 (−0.005, 0.013)	0.015 (0.002, 0.029)	−0.054* (−0.089, −0.021)	0.091* (0.049, 0.132)	0.138* (0.114, 0.162)
South-East Asia	−0.114* (−0.162, −0.065)	0.001 (−0.008, 0.011)	0.003 (−0.014, 0.020)	−0.011 (−0.058, 0.035)	0.049* (0.012, 0.086)	0.125* (0.091, 0.157)
Western Pacific	0.077* (0.059, 0.096)	−0.001 (−0.007, 0.004)	−0.004 (−0.009, 0.002)	−0.019 (−0.050, 0.011)	0.066* (0.032, 0.100)	0.140* (0.115, 0.164)

positive relations between urbanization and LE in males and females are found in the six regions.

DISCUSSION

It has been largely unexplored the spatial distribution and variation of GGLE worldwide. The current study is one of the first that exhibited the spatiotemporal trends in GGLE and examined the effects of air pollution and urbanization on GGLE and gender-specific life expectancy from a global perspective. Further, the geographic disparities in the impacts of these influencing factors on GGLE among six WHO regions can be quantified by the regression coefficients by Bayesian spatiotemporal ecological regression. Several key points can be further discussed as follows.

First, the spatiotemporal trends in GGLE at the global scale are investigated in this study. Some previous studies have been performed on GGLE's distribution at the cross-country level. It was found that GGLE grew rapidly during most of the 20th century. Then, a reversal of this trend has been observed that the GGLE has declined since the 1980s among many developed countries such as Italy [38], France [39], Netherlands [40], Sweden and Japan [9, 41], Canada [42], South Korea [43], and the United States [44]. It also revealed that GGLE trend showed inverted U-curves in most Organization for Economic Co-operation and Development (OECD) countries undergoing three phases, i.e., growth, peak and stability, and decline [45]. Further, it was found that GGLE varied substantially in EU 28 Member States in 2015, which showed that GGLE was 5.4 years on average [46]. In addition, it was found that the GGLE converges in highly developed countries but diverges in

less developed countries [47]. Our findings extend the study on the spatial distribution of GGLE worldwide, forming an evident spatial heterogeneity with a continuously increasing trend of GGLE from 1960 to 2018. Different from previous studies, our results decomposed the spatiotemporal variability of GGLE into three components: the common spatial pattern across the study periods, the overall temporal trend, and local temporal trends. For one thing, the average values of GGLE among regions in Africa and South-East Asia show much lower GGLE, and the Americas, Europe, and Western Pacific exhibit a relatively higher level compared to the global level. For another, most countries present the increase–decrease trend with the peak value of GGLE, similar to the patterns of OECD countries. Further, the distribution of the peak values of GGLE shows similar patterns to the average values of GGLE in the world. In comparison, only 27% of countries show continuous increasing or decreasing trends without a peak GGLE value. These countries are the least developed countries located in Africa, Asia, and Latin America. In sum, our findings indicate that the average level and peak values of GGLE show obvious differences among six WHO regions in the world.

Second, it is evident that women have longer LE than men, and female superiority in LE appears to be one of the most striking features of human health [48–50]. Several factors, such as biological [51] and behavioral factors [52], have been proposed to explain these differences. However, these factors cannot fully explain why GGLE would fluctuate over time [50]. Importantly, social-economic and environmental factors have not been taken into consideration in the gender differences, though these factors are closely related to LE, which have been investigated in extensive studies [12, 53–56]. A previous study probed the difference of social-economic determinants in LE between total LE and female LE, which showed that the fit of the models for the female population is weaker than the respective fits of the models for the entire population, indicating that the parameters should be different in female LE [57]. A recent study revealed the spatial heterogeneity of the relations between LE and *per capita* GDP and pwPM$_{2.5}$ based on the Bayesian regression model [58]. This paper introduces pwPM$_{2.5}$ and urbanization factors as our core independent variables. Using the Bayesian spatiotemporal ecological regression, our findings reveal the significant negative influence of pwPM2.5 and urbanization on GGLE with spatial random effects. Although no significant relations are found between pwPM$_{2.5}$ and LE in males and females, we reveal the negative regression coefficients in females are lower than in males. In general, our finding is in line with previous studies, which showed that adult males had higher exposure to air pollutant factors than females [59–61]. Thus, the current paper indicates that the negative impacts of air pollution on males are more severe than on females, which may positively relate to GGLE. Meanwhile, we find a significant positive influence of urbanization on GGLE with spatial random effects. Urban populations have longer life expectancies than rural populations. A previous study in the U.S. showed that urban life expectancy increased in women faster than men, whereas rural life expectancy decreased in men faster than women [62]. Our findings are consistent with the previous paper that the urbanization factor may be more advantageous to females than males, which may

further result in the significant positive influence of urbanization on GGLE.

Moreover, our findings could provide several implications. Firstly, the average level and peak values of GGLE show obvious differences among WHO regions in the world, and the countries with higher levels of GGLE are mostly related to higher development levels. It could be inferred that the GGLE may keep increasing with social-economic development and worsening air pollution in most regions worldwide. Secondly, it further indicates that the air pollution factor with spatial autocorrelation should consider the influence of GGLE. Further investigations are needed to probe the gender differences in PM$_{2.5}$ pollution. Our modeling presents obvious geographic disparities of the impacts of PM$_{2.5}$ across space. America, Europe, and Western Pacific showed positive relations between pwPM$_{2.5}$ and GGLE, which is in line with the global trend. Interestingly, these regions exhibit a relatively higher level than the global average. In contrast, Africa, Eastern Mediterranean, and South-East Asia showed the opposite trend, indicating that spatial heterogeneity should be highlighted, especially in the world's developing regions. Similarly, the spatial heterogeneity of urbanization influence should also be focused on the regions such as Africa, America, Eastern Mediterranean, and Europe. Furthermore, the coupling relationship between urbanization and air pollution has become a hotspot internationally in sustainable development studies [63]. Developing sustainable urbanization practices with air pollution control is crucial for addressing sustainable development [64]. Our findings further indicated that air pollution and urbanization factors should be considered comprehensively in achieving Sustainable Development Goals and the influencing mechanism of GGLE. Therefore, our investigation may provide a potential solution to narrow the GGLE by coordinating the roles of social-economic growth and improvement of air quality in a society with a fair chance for both men and women to maximize their gaps in life expectancy.

Nevertheless, several limitations and study prospects in this paper should be noted. Firstly, although more accurate human PM$_{2.5}$ exposure data are much needed in the future, the error associated with satellite and simulated PM$_{2.5}$ concentration was assessed and calibrated in this paper. Similarly, we used the death rate from smoking rather than smoking prevalence as a covariate due to the limitation of data sources, which could be improved in future studies. Secondly, the effect of PM$_{2.5}$ and urbanization may be biased due to omitted confounders and spatial confounding [65]. The spatial confounding indicates that unobserved influencing factors may confound the model estimates if they directly impact GGLE and, at the same time, are correlated with the observed covariates. Therefore, this issue should be fully considered to improve the accuracy of model estimation and spatial modeling [66]. Thirdly, the influence of PM$_{2.5}$ and urbanization indicated that the confounders for GGLE are not the same as for life expectancy. Hence, it may need further analysis of GGLE rather than a comparison of the coefficients between males and females. Fourthly, the collinearity results due to the multi-environmental and social-economic factors should be interpreted with caution in ecological studies [67], especially when more influencing factors and covariates are selected in

future papers. Further, unaccounted confounders mentioned above make policy inferences quite difficult. Accordingly, follow-up studies can be performed to fully recognize the mechanism of the spatiotemporal trends in GGLE, especially on the global scale, though several factors have been probed, such as gender inequality [46], Human Development Index [45], invest in health and the gender gap in wages [44], women's status and modernization [10], diseases [68], alcohol and life satisfaction [69], homicides [70], etc. Fifthly, although our study reveals the nonlinearity in the trend in GGLE, the driving mechanism still needs to be thoroughly probed based on the nonlinear hypothesis. Last, this paper only used historical data in our modeling. Hence, prediction and simulation of GGLE variation in space could provide in-depth information and policy implication to meet the future needs of aging societies and improve sustainability in the coming years.

AUTHOR CONTRIBUTIONS

ZR: Conceptualization, Writing—Original draft, Writing—Review and Editing, Funding Acquisition, Project Administration. SW: Conceptualization, Writing—Original draft, Writing—Review and Editing, Data Curation, Investigation, Project Administration. XL: Data Curation, Methodology, Formal analysis, Software, Validation, Visualization. QY: Writing—Review and Editing, Methodology. JF: Data Curation, Writing—Review and Editing, Formal analysis. All authors have read and agreed to the published version of the manuscript. All authors contributed to the article and approved the submitted version.

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CONFLICT OF INTEREST

The authors declare that they do not have any conflicts of interest.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.ssph-journal.org/articles/10.3389/ijph.2023.1605345/full#supplementary-material

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