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Proximate determinants of particulate matter ($PM_{2.5}$) emission, mortality and life expectancy in Europe, Central Asia, Australia, Canada and the US

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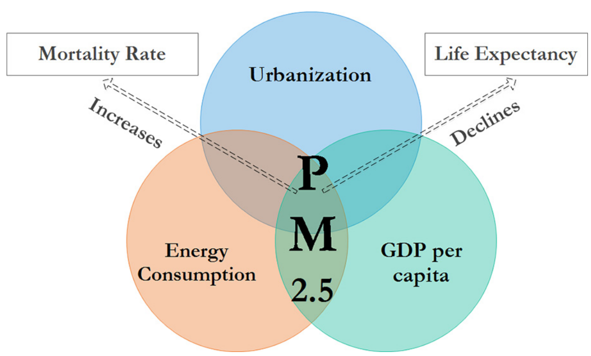
HIGHLIGHTS

- Determinants of ambient air pollution, mortality, and life expectancy were examined in 54 countries.
- A GLS random-effects model estimation with first-order autoregressive [AR(1)] was used in the study.
- Long-term increase in income level by 1% declines mortality rate by 0.01%.
- Inversed-U shaped curve between $PM_{2.5}$ and income level was observed at a turning point of US$ 48,061.
- Ambient air pollution contributes significantly to reducing life expectancy and increasing mortality.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: The growing concern with environmental related impacts on mortality and morbidity means that the conceptual framework of environment-health-economic policy nexus is salient in the global debate on air pollution.
Objectives: With time series data spanning 2000–2016, this study explored the proximate determinants of ambient air pollution, mortality, and life expectancy in North America, Europe & Central Asia, and East Asia & Pacific regions.
Methods: The study applied historical data on urban population, total pollution, energy consumption, GDP per capita, life expectancy, mortality rate and industrial $PM_{2.5}$ emissions to develop six parsimonious models using the generalized least squares (GLS) random-effects model estimation with first-order autoregressive [AR(1)] disturbance across 54 countries.
Results: An increase in income level by 1% declined mortality rate by 0.01% and increased longevity by ~0.02% (95% Confidence Interval [CI]) in the long-run. An increase in industrial $PM_{2.5}$ emissions per capita by 1% decreased life expectancy by 0.004% and mortality rate by 0.02% (95% CI). Intensification of energy consumption and its related services by 1% were found to increase industrial $PM_{2.5}$ emissions by 0.42–0.45% (95% CI). An inversed-U shaped curve between $PM_{2.5}$ emissions per capita and income levels was found at a turning point of US$ 48,061. The validity of an environmental Kuznets curve hypothesis between ambient air pollution and urbanization was confirmed, while a rapid increase in population had a significant positive impact on ambient air pollution.
Conclusion: Ambient air pollution contributes significantly in reducing life expectancy and increasing mortality.

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However, sustained economic development, along with energy efficiency, and sustainable urban settlement planning and management are potential options for reducing ambient air pollution while improving quality of life and environmental sustainability.

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1. Introduction

Ambient air pollution has become a public health concern, due to its impact on mortality and morbidity. It is estimated that seven million people die annually from the combined effect of indoor and outdoor air pollution (WHO, 2014). Air pollution-attributable mortality results from morbidity, such as stroke, ischaemic heart disease, chronic obstructive pulmonary disease, lung cancer and acute lower respiratory infection in children (WHO, 2012). Studies have examined the impact of ambient air pollution on morbidity (Cohen et al., 2017; WHO, 2016), mortality (Burnett et al., 2018; Mueller et al., 2016; Pope et al., 2018) and longevity (Balakrishnan et al., 2019; Pope III et al., 2009; Schwartz et al., 2018). Although all studies have triggered public health concerns in relation to the impact of ambient air pollution on mortality rate, life expectancy and morbidity, however, the results are inconsistent due to differences in demographic characteristics, model estimation methods and the nature of data (i.e. experimental, cross-sectional, time series or panel data) employed. The by-product of unsustainable planning and management policies from energy, agricultural, transport and industrial sectors often spur excessive air pollution (WHO, 2014). Air pollution is, therefore, an indicator of sustainable development, since, policies that address air pollution improve health outcomes and reduce greenhouse gas (GHG) emissions (WHO, 2016). A recent study found a 90% decline in household air pollution attributable to a reduction in traditional biomass energy consumption, mainly due to rapid urban population growth (Zhao et al., 2018). The Intergovernmental Panel on Climate Change (IPCC) 5th assessment report confirms income level, population, energy, and GHG intensity as the immediate drivers of environmental pollution. However, existing literature on the nexus between environment and health outcomes hardly consider these relevant variables, hence, leading to omitted-variable bias.

As a contribution to the global debate on air pollution, this study for the first time examined the determinants of industrial-related atmospheric emissions of particulate matter (PM), mortality, and life expectancy, with the addition of income level, population, urban population, and energy consumption to control for omitted-variable bias. The study further tested the validity of the environmental Kuznets curve (EKC) hypothesis of industrial PM emissions versus income level and urban population, respectively. Due to data availability, the study was limited to 54 countries for the period between 2000 and 2016. There are several estimation techniques utilized for cross-sectional time series models, however, only few methods can control for missing data observations, serial correlation and unbalanced panels. In this context, the study employed the generalized least squares (GLS) random-effects model proposed by Baltagi and Wu (1999) to develop six conceptual frameworks which incorporate the concept of sustainable development in the hypothesis. A similar estimation method was applied to examine the nexus between economic activity and air pollution (Davis et al., 2010). Our study demonstrated that ambient air pollution, demographic characteristics, energy and socio-economic policies have implications for health outcomes in Europe, Central Asia, Australia, Canada and the US.

2. Materials and methods

2.1. Data

Table 1 presents the description of data variables. Seven data series with an annual periodicity spanning from 2000 and 2016 from 54 countries in North America, Europe & Central Asia, and East Asia & Pacific regions were employed in this study. The countries include Australia, Albania, Armenia, Austria, Azerbaijan, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kazakhstan, Kyrgyzstan, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, Montenegro, Netherlands, Norway, Poland, Portugal, Republic of Moldova, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Tajikistan, Macedonia, Turkey, Turkmenistan, Ukraine, United Kingdom, US, and Uzbekistan. The 54 countries were selected due to data availability. Data on $PM_{2.5}$ (kg per annum) are annual atmospheric industrial PM emissions collated from the Centre on Emission Inventories and Projections (CEIP, 2018) which operates the United Nations Economic Commission for Europe (UNECE) and European Monitoring and Evaluation Programme (EMEP) emission database. Data series on crude death rate (per 1000 people), life expectancy at birth (years), total urban population, total population, energy consumption (kg of oil equivalent per capita), and GDP per capita (current US$) were obtained from the World Bank (2018) development indicators database. The selection of the data series was based on the targets outlined in the Sustainable Development Goals (SDGs) 3, 7–8, and 11–13 —reducing air-pollution attributable mortality and preventable diseases; reducing the reliance on fossil fuel energy technologies and increasing the share of clean and renewable energy sources; ensuring sustainable economic development; ensuring sustainable human settlement; reducing unsustainable consumption and production patterns; and mitigating climate change and its impacts (United Nations, 2015).

2.2. Data analysis

Due to the unequal distribution of the data series for the 54 countries, the study employed the GLS random-effects model estimation with locally best invariant (LBI) test statistic proposed by Baltagi and Wu (1999). The GLS random-effects model fits longitudinally based regression with first-order autoregressive white noise [AR(1)] and it's capable of controlling for missing data, unbalanced panel data, serial correlation and country-specific random effects. As a data pre-processing technique, all the data series were transformed logarithmically (ln) to provide the variables with a constant variance. In model 1 presented in Eq. (1), ambient air pollution of country i in year t ($\ln PM_{2.5i,\,t}$) was regressed on urban population ($\ln URBAN_{i,\,t}$), energy consumption ($\ln ENERGY_{i,\,t}$), income level ($\ln PGDP_{i,\,t}$) and the second-degree polynomial of income level ($\ln PGDP^2{}_{i,t}$). The empirical specification of the model used is expressed as:

$$\text{Model 1}: \ \ln PM_{2.5i,t} = \alpha + \beta_1 \ \ln URBAN_{i,t} + \beta_2 \ \ln ENERGY_{i,t} + \beta_3 \ \ln PGDP_{i,t} + \beta_4 \ \ln PGDP^2{}_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (1)$$

where α is the constant, $\beta\,'s$ are the estimated parameters, $\phi_{i,\,t}$ is the

Table 1
Description of data series in Europe, Central Asia, Australia, Canada and USA.

Variable	Code	Unit
Particulate matter ($PM_{2.5}$)	PM2.5	kg
Crude death rate	DEATH	per 1000 people
Life expectancy at birth, total	LIFE	years
Urban population	URBAN	number
Total Population	TPOP	number
Energy consumption	ENERGY	kg of oil equivalent per capita
GDP per capita	PGDP	current US$

country-specific random effect assumed to be uncorrelated with the covariates of the regressors and the error term, which follows independent, identically distributed (i.i.d.) process with zero mean and variance, and disturbance $\varepsilon_{i,\,t} = \rho\varepsilon_{i,\,t-1} + \eta_{i,\,t}$.

In model 2, ambient air pollution was regressed on energy consumption, income level and the second-degree polynomial of income level, expressed as:

$$\text{Model 2}: \ \ln PM_{2.5\,i,t} = \alpha + \beta_1 \ \ln ENERGY_{i,t} + \beta_2 \ \ln PGDP_{i,t} + \beta_3 \ \ln PGDP^2{}_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (2)$$

In model 3, ambient air pollution was regressed on urban population and energy consumption, expressed as:

$$\text{Model 3}: \ \ln PM_{2.5\,i,t} = \alpha + \beta_1 \ \ln URBAN_{i,t} + \beta_2 \ \ln ENERGY_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (3)$$

In model 4, ambient air pollution was regressed on the total population ($\ln TPOP_{i,\,t}$) and energy consumption, expressed as:

$$\text{Model 4}: \ \ln PM_{2.5\,i,t} = \alpha + \beta_1 \ \ln TPOP_{i,t} + \beta_2 \ \ln ENERGY_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (4)$$

In model 5, ambient air pollution per capita was regressed on income level and the second-degree polynomial of income level to test for the EKC hypothesis expressed as:

$$\text{Model 5}: \ \ln PM_{2.5}C_{i,t} = \alpha + \beta_1 \ \ln ENERGY_{i,t} + \beta_2 \ \ln PGDP_{i,t} + \beta_3 \ \ln PGDP^2{}_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $PM_{2.5}$ per capita ($\ln PM_{2.5}C_{i,\,t}$) was calculated by dividing $PM_{2.5}$ by the total population.

In model 6, life expectancy ($\ln LIFE_{i,\,t}$) was regressed on ambient air pollution per capita and income level, expressed as:

$$\text{Model 6}: \ \ln LIFE_{i,t} = \alpha + \beta_1 \ \ln PM_{2.5}C_{i,t} + \beta_2 \ \ln PGDP_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (6)$$

In model 7, mortality rate ($\ln DEATH_{i,\,t}$) was regressed on ambient air pollution per capita and income level, expressed as:

$$\text{Model 7}: \ \ln DEATH_{i,t} = \alpha + \beta_1 \ \ln PM_{2.5}C_{i,t} + \beta_2 \ \ln PGDP_{i,t} + \phi_{i,t} + \varepsilon_{i,t} \quad (7)$$

While the seven models were validated using the marginal effects post-estimation technique, the EKC hypothesis was verified using the Utest algorithm procedure by Lind and Mehlum (2010) expressed as:

$$PM_{2.5}C_{i,t} = \alpha + \beta_1 PGDP_{i,t} + \beta_2 PGDP^2{}_{i,t} + \varepsilon_{i,t} \quad (8)$$

where $PM_{2.5}C_{i,\,t}, PGDP_{i,\,t}, PGDP^2{}_{i,t}$, α and $\varepsilon_{i,\,t}$ are explained in the previous equations.

3. Results

Figs. 1–4 present the mean distribution of pollutants, energy consumption, income level, urbanization, population, life expectancy and death rate from 2000 to 2016 in 54 countries in Europe, central Asia, Australia, Canada and USA. The minimum average annual industrial $PM_{2.5}$ emissions occur in Monaco at 3381 kg while the highest emission occurs in the US at 4,721,297,957 kg (Fig. 1). Fig. 2(a) shows the minimum average energy consumption occurs in Tajikistan at 325 kg of oil equivalent per capita, while the maximum energy consumptions occur in Iceland at 14,462 kg of oil equivalent per capita. Tajikistan has the minimum average income level at US$ 592 while the highest is Monaco at US$ 130,851 [Fig. 2(b)]. Liechtenstein has the lowest mean urban population of 5188 people compared to the US with the highest urbanized population of 244,178,564 people [Fig. 3(a)]. The minimum mean population occurs in Monaco with 35,547 people while the US has the highest population of about 303,408,340 people [Fig. 3(b)]. The average life expectancy [Fig. 4(a)] at birth is the lowest in Turkmenistan (66 years) and highest in Iceland and Switzerland (82 years). On the contrary, the minimum mean death rate of 5 per 1000 people occurs in Uzbekistan while the highest death rate of 15 per 1000 people occurs in Bulgaria and Ukraine [Fig. 4(b)].

Table 2 shows the GLS random-effects model estimation results with AR(1) disturbance. Different observations ranging from 795 to 905 were included with 54 countries, and the regressors explained approximately 17–69% of variations in the response variables ($PM_{2.5}$, $PM_{2.5}$ per capita, life expectancy and death rate) estimated by the overall R-squared value. All coefficients from the six models had the expected signs and were statistically significant at 1, 5, and 10% level. The empirical results found 0.72 and 0.79 coefficients on the nexus between $PM_{2.5}$ and urban population, signifying that a 1% increase in urban population increases industrial $PM_{2.5}$ emission levels by 0.72–0.79%. To determine the effect of urban sprawl in developed economies, the study employed the pathway to estimating the environmental Kuznets curve hypothesis with results presented in Table 3. As an addendum, the study confirmed the existence of an inversed U-shape curve between industrial $PM_{2.5}$ emissions and urbanization at a turning point of 162,000,000 people. Similarly, the study found a positive coefficient (0.81) on total population, which is relatively higher than the coefficients on urban population, reflecting the stronger effect of population on air pollution.

Empirically, a 1% increase in population escalates the levels of $PM_{2.5}$ by 0.81%. To test the validity of the EKC hypothesis, the study employed two different response variables (total industrial $PM_{2.5}$ emissions and $PM_{2.5}$ emissions per capita) as a proxy for ambient air pollution. The latter response variable for estimating the EKC hypothesis was divided by the total population of each country. The estimated coefficients (0.80 and 0.83) on GDP per capita for both response variables (pollutants) were positive while the coefficients (−0.05) on the squared of GDP per capita were negative, hence, confirming the validity of the EKC hypothesis. To corroborate the hypothesis, the study further employed the Utest estimation technique presented in Table 3. The Utest validated the existence of an inversed-U shaped curve between $PM_{2.5}$ per capita and income level —at a turning point of US$48,061. The results are consistent with Sarkodie and Strezov (2019b) who reported a turning point of US$48,101 for selected developed countries. From an empirical perspective, an increase in country-specific income level intensifies ambient air pollution by almost 8% ($-0.5^*PGDP/PGDP^2$) and declines after reaching a turning point of US$48,061. The three coefficients on energy consumption from the estimated regression produced varied results from 0.42 to 0.45, revealing a positive effect. Thus, intensification of energy consumption and its related services increase $PM_{2.5}$ by 0.42–0.45%.

After examining the determinants of fine particulate matter, the study proceeded to test the nexus between life expectancy, mortality, income level and exposure to ambient air pollution. The coefficient (0.019) on GDP per capita versus life expectancy is positive, confirming the positive impact of a long-term increase in income level on longevity by ~0.02%. In contrast, long-term increase in GDP per capita declines mortality rate by 0.01%. Comparatively, growth in income levels in both scenarios shows a domineering role in improving life expectancy (~0.02%) compared to a reduction in mortality rate (0.01%). While a 1% increase in industrial $PM_{2.5}$ emissions per capita decreases life expectancy by 0.004%, an increase in the same increases mortality rate by 0.02%.

3.1. Model validation

The validity of the model is essential for making unbiased statistical inferences. Although there were gaps in the data series for some countries considered in the study, only Fisher-type tests could be used for testing panel unit root. First generational panel unit root tests, like Im-

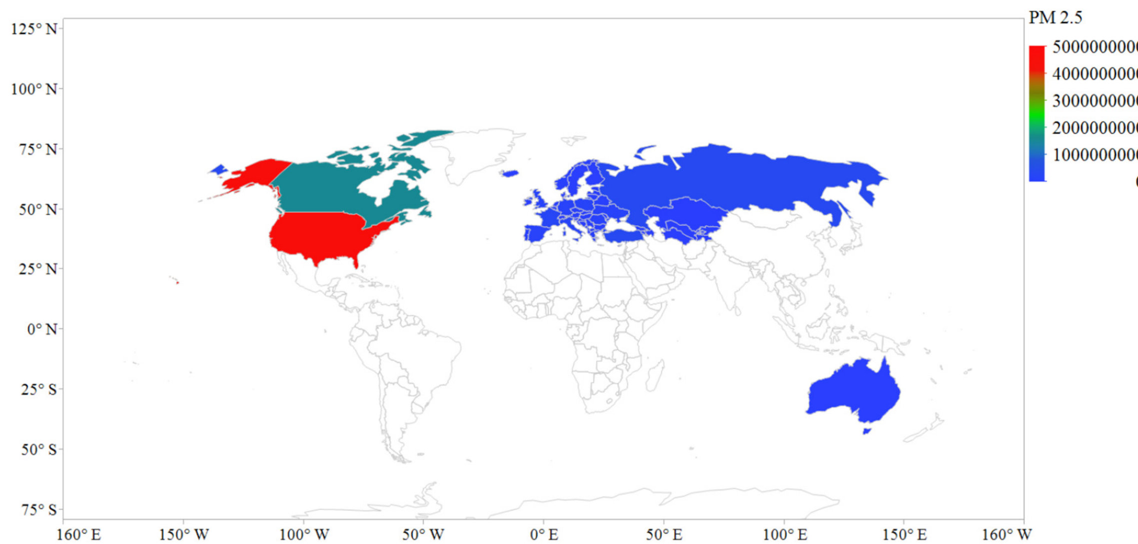

Fig. 1. Mean geographical distribution of Pollutants — $PM_{2.5}$ [kg].

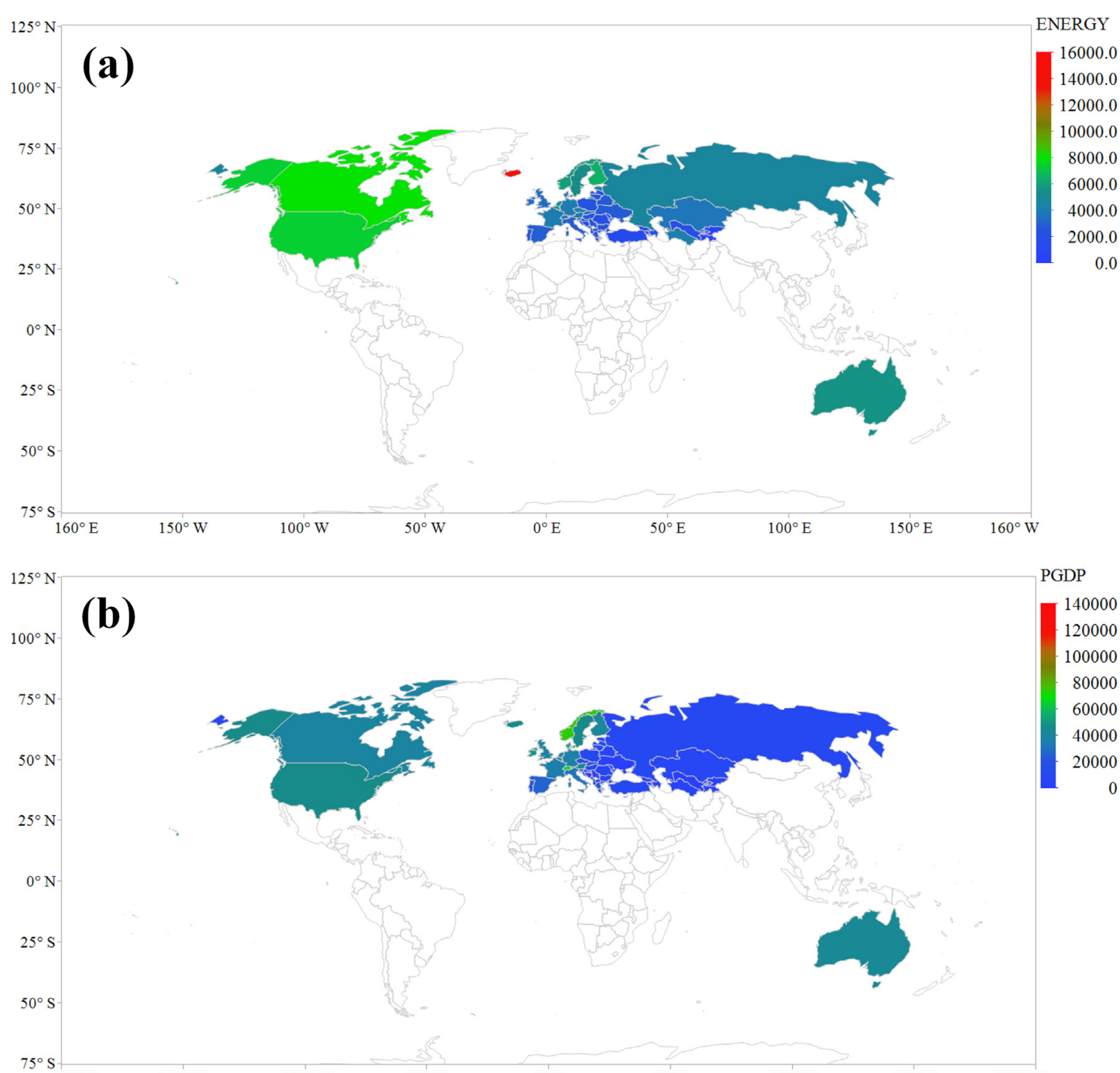

Fig. 2. Mean geographical distribution of (a) Energy consumption [kg of oil equivalent per capita] (b) GDP per capita [current US$].

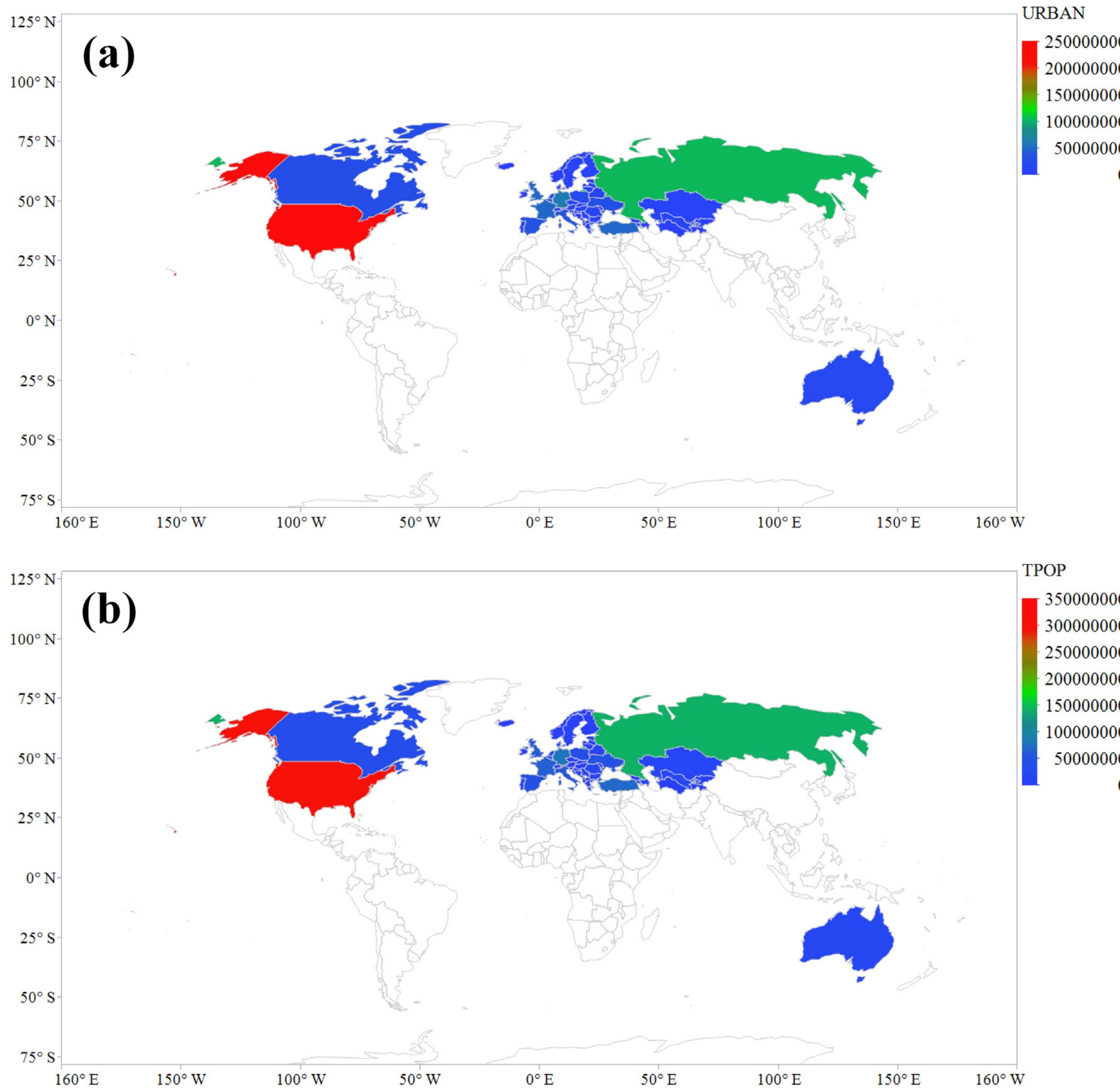

Fig. 3. Mean geographical distribution of (a) Urbanization (b) Total population.

Pesaran-Shin which requires no gaps in observations, and Breitung, Im-Pesaran-Shin, Hadri LM, Levin-Lin-Chu, Harris-Tzavalis and other second generational panel unit root tests require a strongly balanced panel data. However, such conditions are not required by the Fisher-type tests. The estimated panel unit root using Fisher-type tests like Dickey-Fuller and Phillips-Perrons rejected the null hypothesis that all the panel contains unit root at first difference, hence, confirmed the data series were integrated of order one, I(1) [Supplementary Material]. Due to the data limitations of the study, an econometric estimation method was adopted in STATA Version 15 capable of controlling for the unbalanced panel with missing data. The estimated Baltagi and Wu (1999) locally best invariant (LBI), modified Bhargava et al. (1982) Durbin-Watson test statistics were within the acceptable range, thus, validating the robustness of the six models. Fig. 5 presents the conditional marginal effects with a 95% confidence interval (CIs). The marginal effect is a post-estimation technique utilized after estimating the proposed six models. It outputs corresponding statistics from predicting previously fit model using either fixed and average covariates or the integration of remaining covariates (Williams, 2012). The plots of the estimated marginal effects of all the six models depicted in Fig. 5 were within the 95% confidence interval bands, hence, confirming the stability of the estimated models.

4. Discussion

Rapid urbanization has a long history with increasing levels of ambient concentration of air pollution, due to its associated socio-economic and environmental challenges. This study, in line with previous studies (Wang et al., 2018; Wang et al., 2019), demonstrated that rapid growth in urban population increases industrial PM emissions at the initial stages but air pollution declines after urban sprawl exceed 162 million population. Except for the US with over 244 million urban population, the available data shows that countries like the Russian Federation, Germany, United Kingdom, France, Turkey, Italy, Spain, Ukraine and Canada with expanded urban dwellers below 162 million population have high levels of industrial induced ambient air pollution. In contrast, industrial air pollution was found to decline in America and European countries with high urban population compared to developing countries (Yang et al., 2018). Thus, rapid urban population growth has a mitigating effect on industrial PM emissions in developed countries (Wang et al., 2019). The mitigating effect stems from the stringent environmental regulations and improved industrial-related abatement technologies instituted in urban areas of developed countries.

The significant positive impact of population on ambient air pollution is consistent with Chen et al. (2018). Increasing population growth

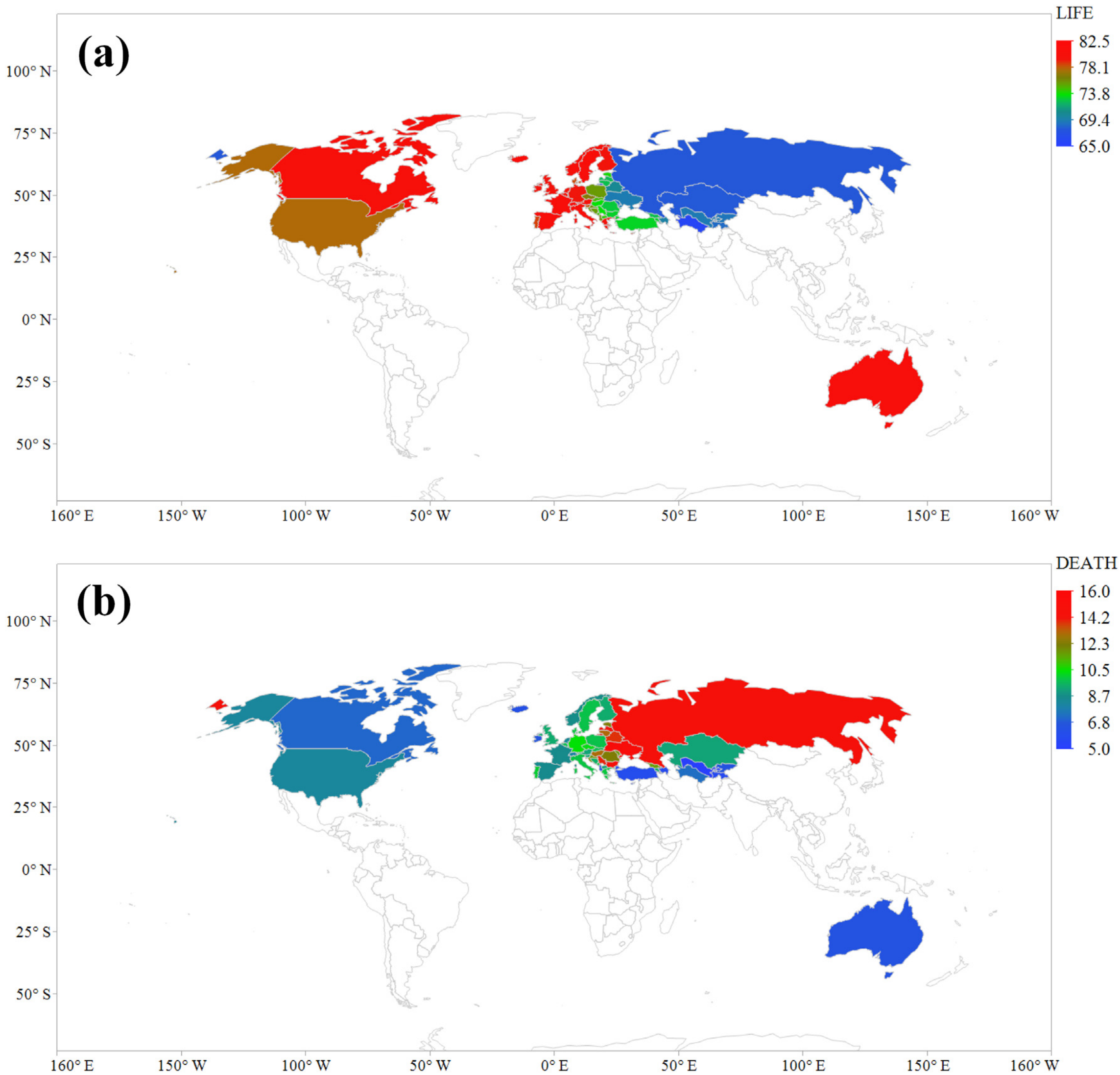

Fig. 4. Mean geographical distribution of (a) Life expectancy at birth [years] (b) Crude Death rate [per 1000 people].

Table 2
GLS random-effects (RE) model estimation results with AR(1) disturbance.

Variables	$PM^a_{2.5}$	$PM^b_{2.5}$	$PM^c_{2.5}$	$PM_{2.5}C$	Life expectancy	Mortality rate
Urban population	0.79^{**} [0.07]	0.72^{**} [0.08]	–	–	–	–
Energy consumption	0.42^{**} [0.06]	0.42^{**} [0.06]	0.45^{**} [0.06]	–	–	–
GDP per capita	0.80^{**} [0.12]	–	–	0.83^{**} [0.13]	0.019^{**} [0.001]	-0.01^{*} [0.01]
Squared of GDP per capita	-0.05^{**} [0.01]	–	–	-0.05^{**} [0.01]	–	–
$PM_{2.5}$ per capita	–	–	–	–	-0.004^{**} [0.002]	0.02^{**} [0.01]
Total population	–	–	0.81^{**} [0.09]	–	–	–
Constant	−1.63 [1.25]	2.56^{***} [1.37]	0.64 [1.54]	-2.57^{**} [0.56]	4.160^{**} [0.011]	2.32^{**} [0.06]
Prob > χ^2	0.00^{**}	0.00^{**}	0.00^{**}	0.00^{**}	0.00^{**}	0.01^{*}
N	795	795	795	905	893	894
ID	52	52	52	54	53	54
R^2	0.67	0.65	0.65	0.17	0.69	0.19

a, b, c represent models 1–3, Parenthesis [ ] denotes the standard error, *ID* = Number of countries, *N* = Number of observations, R^2 = overall R-squared, $^{**},^{*},^{***}$ rejection of the null hypothesis at 1, 5 and 10% significance level.

Table 3
Utest relationship for validating EKC hypothesis.

	Lower bound	Upper bound	Turning point
Interval	US$138[a]	US$192,989[a]	US$48,061[a]
	5036[b]	265000000[b]	162000000[b]
Slope	0.00[a]	0.00[a]	
	0.00[b]	0.00[b]	
t-Value	8.64[a]	−8.62[a]	
	24.71[b]	−13.31[b]	
$P > t$	0.00[a,**]	0.00[a,**]	
	0.00[b,**]	0.00[b,**]	

Test: H_1: Inverse U shape vs. H_0: Monotone or U shape.
[a] Represents GDP per capita.
[b] Represents urbanization.
** Denotes the rejection of the null hypothesis.

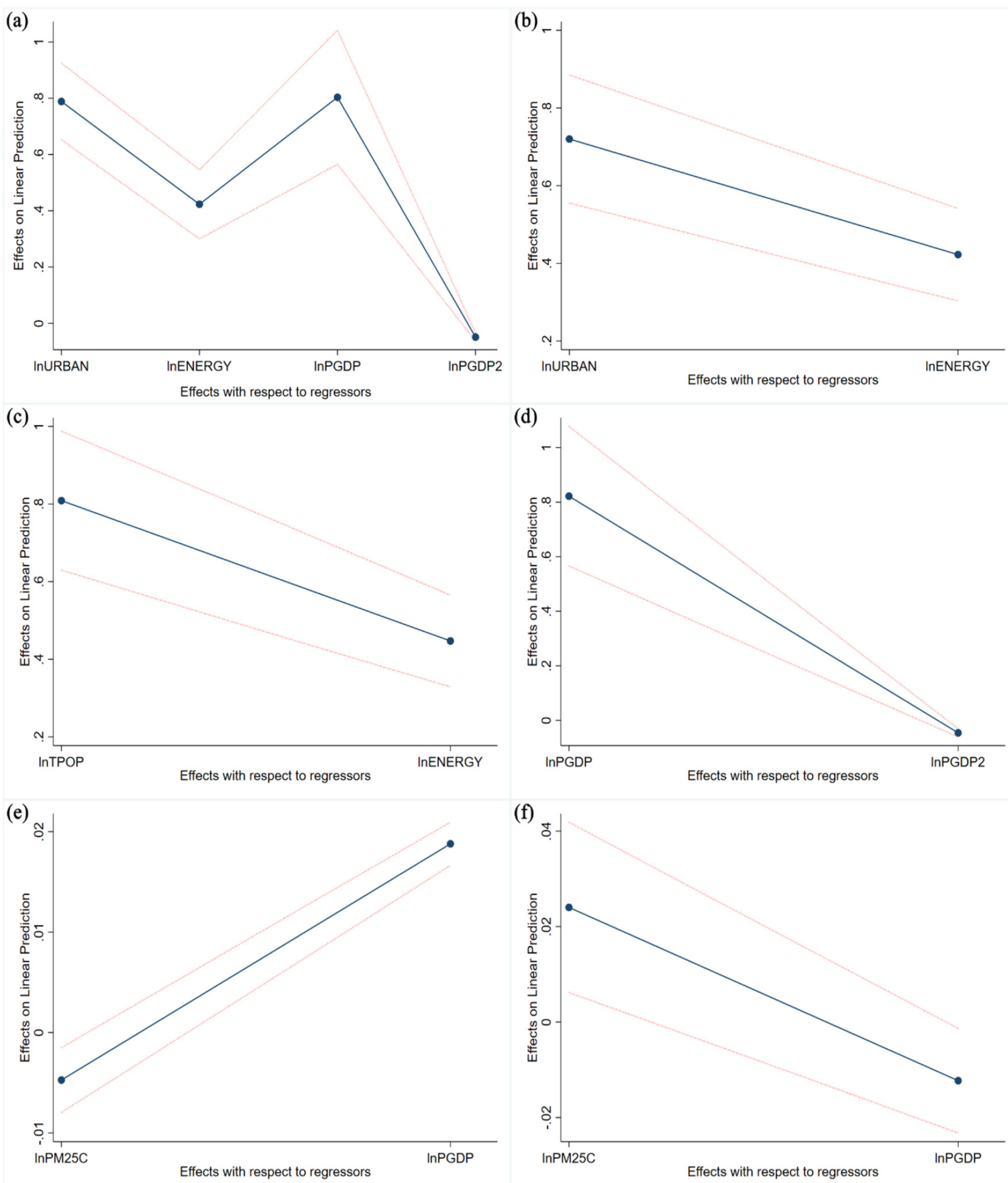

Fig. 5. Conditional Marginal Effects with 95% CIs (a) Model 1 (b) Model 2 (c) Model 3 (d) Model 4 (e) Model 5 (f) Model 6.

increases the demand for land, food, transport, energy, natural resources and environmental infrastructures, which could intensify human and socio-economic activities spurring ambient air pollution. Rapid population growth has affected land-use and food production systems through intensification and extensification, leading to ecologically damaging challenges due to intensive production and consumption patterns (Preston, 1996). A strong feedback equilibrating mechanism was found between population growth and air pollution (Cramer, 2002). Population growth in developed countries with higher levels of air pollution is relatively slow compared to developing countries (Cramer, 2002). In terms of sectoral contribution, population growth plays a critical role in agrarian transformations compared to industrial pollution. While rapid population requires reallocation of natural resources to meet the growing demand for food, the same logic does not apply when considering industrial transformations (Preston, 1996). Hence, the effect of population growth on ambient air pollution is intensive in agrarian-dependent economies compared to industrialized economies.

Energy consumption remains the backbone of economic development, however, unsustainable production and consumption patterns have been linked to environmental pollution and degradation (Sarkodie and Strezov, 2018). This study found a positive relationship between industrial $PM_{2.5}$ emissions and energy consumption, consistent with Chen et al. (2018). The empirical results depict that energy consumption and income levels are intertwined. The nexus between industrial air pollution and income levels produced an inversed-U shape, hence, validating the EKC hypothesis. The underlying reasons for the observed inversed-U shape can be attributed to environmental awareness, stringent industrial-related emission laws, modern energy sources and the introduction of advanced technologies like carbon, capture and storage in high-income countries (Blanco et al., 2014; Edenhofer et al., 2011; Owusu and Asumadu, 2016). The concentrations of industrial $PM_{2.5}$ in relation to energy consumption patterns were relatively high in the lower-middle and low-income countries (Chen et al., 2018). Energy sector and its related services are by far the major contributors to ambient air pollution (IEA, 2016). The level and trend of energy-related air pollution depend on the phase of a country's economic development (pre-industrial, industrial and post-industrial sector). At the initial stages of economic development, demographic changes, such as rural-urban migration have the tendency of increasing the concentration of energy-related air pollution. Most industrialized economies depend on fossil fuel energy technologies for power generation and industrial production —increasing the levels of industrial and energy-related pollutants. This stage is characterized by heavy manufacturing, energy-intensive, and labour-intensive production with the aim of increasing the production of goods and services but with limited energy efficient technologies (Xu et al., 2016). Lifestyle changes and consumption patterns associated with wealth may increase the demand for more energy services, such as electricity for appliances and oil for transportation purposes, which may potentially escalate air pollution. As income level rises further to a turning point of US$48,061 per annum, households switch from polluting energy technologies to modern and cleaner energy sources, leading to a decline in industrial PM emissions. Ambient air pollution declines in services and decarbonized economies due to stringent environmental policies, transfer of polluting industries to developing countries, technological advancement, energy efficiency, conservation and management options among the population (Dasgupta et al., 2002; Sarkodie and Strezov, 2019a).

Further empirical evidence shows that sustained income level increases life expectancy and decreases the mortality rate. 1% reduction in industrial emissions of particulate matter was found to increase life expectancy by 15% (Pope III et al., 2009). The monetary cost involved in reducing ambient air pollution in high-income countries has a positive effect on life expectancy and quality of life. Sustained income levels increase access to, inter alia, basic needs, quality healthcare, and education. Economic theory links higher income levels to consumption patterns —as such, improving household income levels and standard of living improves quality of life by reducing undesirable mortality and morbidity rates.

This study further observed a significant positive relationship between mortality rate and industrial $PM_{2.5}$ emissions, consistent with previous studies (Burnett et al., 2018; Lin et al., 2016; Pope III et al., 2009), which showed that air pollution increases the risk of mortality from stroke, cardiovascular and respiratory diseases. On the contrary, this study found a negative nexus between life expectancy and industrial PM emissions. The toxicity and adverse effects of ambient air pollution also depend on the economic status of countries and the magnitude of concentration. A study showed that ambient air pollution increases morbidity substantially in low- and middle-income countries due to increasing levels of industrial $PM_{2.5}$ emissions, demographic and epidemiological changes (Cohen et al., 2017). Indoor air pollution is visible in low-income countries with an overreliance on traditional biomass, which leads to premature deaths from acute lower respiratory infection and pneumonia in children and mortality from lung cancer and chronic obstructive pulmonary diseases among adults (DiSano, 2002).

4.1. Limitations of the study

The empirical results from the estimated models remain valid based on the following limitations of the study. First, due to the unequal spaced observations and unbalanced characteristic of the panel data used in this model, most first generational and second generational panel unit root tests could not be applied, hence, there are uncertainties about controlling for cross-sectional dependence. However, the estimation technique employed accommodated for pre-estimation issues associated with the data. Second, there are currently no available critical values to compare Baltagi-Wu LBI test statistics for diagnostics after model estimation, however, marginal effects estimation techniques were utilized to cross-validate the estimated models. Notwithstanding, all the empirical results were consistent with energy, environment and health economics literature. The conceptual framework developed in this study utilized a parsimonious model which incorporated the SDGs in the hypothesis, therefore, useful for all studies on environmental and health economics and "nexus" testing.

5. Conclusion

Industrial PM emissions cause ambient air pollution, which is an environmental risk factor that affects health outcomes. Long-term exposure increases mortality, morbidity and reduces life expectancy. This study examined the proximate determinants of industrial $PM_{2.5}$ emissions and the effect on life expectancy and mortality from 2000 to 2016 in Europe, Central Asia, Australia, Canada and the US. While evidence shows that sustained income levels increase life expectancy and decrease mortality rates, ambient air pollution in effect increases mortality rate. Economic development and energy consumption were found to increase the concentration, toxicity, and adverse effect of ambient air pollution. The study confirmed an inversed-U shaped relationship between rapid urbanization and ambient air pollution. Urban sprawl was found to occur at the initial stages of economic development and may trigger higher levels of urban pollution without careful urban settlement planning and management. Urban-related ambient air pollution begins to subside when the urban population attains its carrying capacity and authorities begin to promote, inter alia sustainable human settlements planning, land-use, capacity building, sustainable energy and transportation system. Further studies are needed to validate the empirical results of this study with different air pollutants and income groups.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.05.278.

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