Bayesian Spatio-temporal Analysis of Greenhouse Gas Emissions in Africa

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Research Article

Keywords: greenhouse gases, climate change, global warming, spatio-temporal analysis

DOI: https://doi.org/10.21203/rs.3.rs-694485/v1

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Abstract

Global warming is a driver of climate change and is attributed to the increasing concentration of greenhouse gases in the atmosphere due to human activities. Although Africa contributes the least to global greenhouse gas emissions, its emissions are still on the increase. This study analyzes the spatial effect, temporal effect, and the interaction of these effects on these emissions in Africa. A 27-year greenhouse gas emissions data of some selected African countries was studied using Bayesian spatio-temporal analysis within a Bayesian framework. Inference was based on integrated nested Laplace approximation implemented using the R-INLA package in R. Various subsets of spatio-temporal models were fitted, including those that accounted for boundary shared among countries. Results show that models with the spatio-temporal interaction effect outperform models that did not take this effect into account, confirming findings from existing literature. Findings from this study also revealed that the boundary shared among countries impacts greenhouse gas emissions. Countries that are less likely to have high greenhouse gas emissions but shared boundaries with those likely to have high estimates eventually had a high estimate of emissions over a long period. Controlling and reducing greenhouse gas emissions in Africa should be a collective effort, particularly among countries sharing boundaries.

Keywords: greenhouse gases, climate change, global warming, spatio-temporal analysis

Introduction

Stabilizing the global average temperature is the beauty of greenhouse gases (GHGs) presence in the atmosphere. However, this is changing into being ugly over the years because of their alarming increasing concentration in the atmosphere. Many researchers have traced this increase to the anthropogenic emissions of these GHGs [Stott et al., 2000; Leila, 2013; Stocker, 2013; Niang et al., 2015]. Edenhofer et al. [2014] reported an increase of 81% in anthropogenic emissions of GHGs since 1970. Over the years, global warming attributed to the anthropogenic emission of greenhouse gases has been of topmost concern. By 2100, the Intergovernmental Panel on Climate Change (IPCC) predicts 1.8°-3.9°C increase in average global temperature (IPCC, 2007c). Global warming contributes significantly to climate change that has negative consequences such as extremely high temperature, drought, heatwaves, melting of ice, rise in sea level, flooding, and much more [Koneswaran and Nierenberg, 2008; Leila, 2013].

Africa as a continent has been at the receiving end of the negative impacts of global warming the most [Bewket, 2012; IPCC, 2014]. Warmer temperatures and reduced rainfall in Tanzania caused about 49% loss of ice in Mt. Kilimanjaro between 1976 and 2002, resulting in the drying up of most rivers around it [Ngaira, 2007]. Without curbing the increase in the emission of GHGs, prediction reveals that there will be no ice in Mt. Kilimanjaro, the highest mountain in Africa, in 2033. These may, in turn, affect the revenue of Tanzania as the mountain, which is a source of tourist attraction, serves as a means of revenue generation for the country [Vastag, 2009]. Darghouth and Bouattour [2008] reported that Tunisia is most likely to experience a decrease in annual precipitation by 2030 and attain an increase of 2.1°C in its mean temperature by 2050. Consequently, the risk of water scarcity will be high. And, in turn, harm the inhabitants of the country.

Between 2000 and 2016, there was a significant decrease in the yield of crops in West Africa as a result of the negative impacts of GHGs emissions on crop production [Osabohien et al., 2019]. According to the IPCC, Africa’s agriculture sector is threatened, especially in West Africa. The threat is due to the reduced output of crop yield and production linked to much increase in the number of hot days Africa will experience. These signal that there will be reduced precipitation, and its prolongation will lead to drought. However, the high tendency to reduce crop yield will not leave a good imprint as the demand for food will surpass the food supply by numerous amounts. This paints a picture of food scarcity that may likely explode into famine if not handled carefully. By 2080, as a result of climate
change, over 100 million people will be prone to hunger, with 80% coming from Africa (Carter, 2007).

In addition to these effects, GHG emissions harm the health and well-being of humans. According to World Health Organization, extreme heat causes asthma, respiratory and cardiovascular diseases to increase. Respiratory disease, in particular, increases among children during heatwave (Xu et al., 2012). Activities such as the burning of fossil fuels, coal, natural gas, and oil contribute to GHGs emissions (Bruckner et al., 2014), and emissions related to fossil fuels is accountable for about 65% of excess mortality rate attributable to air pollution (Lelieveld et al., 2019). In Africa, increasing carbon emissions has been found to have a significant effect on child mortality (Shobande, 2020).

Many studies report that Africa contributes the least to the world’s total GHGs emission (Bewket, 2012; IPCC, 2014; Adzawla et al., 2019). However, there has been a continuous increase in the anthropogenic emission of GHGs in Africa. In East Africa, the total GHGs emission increased by 42% between 1990 and 2011. Also, West Africa recorded a 17% increase in GHGs emissions between 1990 and 2014, with Nigeria contributing about 46% of these emissions (USAID, 2011, 2019). By 2050, the projection of GHG emissions in sub-Sahara Africa will increase by as much as 50% (Leimbach et al., 2018), and double-fold increase in Africa as a whole (van der Zwaan et al., 2018). The IPCC state that “Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic (produced by humans) greenhouse gas emissions”. According to the United Nations Framework Convention on Climate Change (UNFCCC), the main GHGs are carbon dioxide ($CO_2$), methane ($CH_4$), nitrous oxide ($N_2O$) and fluorinated gases (per-fluorocarbons (PFCs), hydro-fluorocarbons (HFCs), and sulphur hexafluoride ($SF_6$)).

Several studies have looked into the analysis of GHG emissions in Africa. Energy consumption based on fossil fuel, agriculture production, and other determinants contribute to $CO_2$ emissions in North Africa and some selected countries in East and South Africa (Siti, 2014; Umar et al., 2021). In addition, Olubusoye and Musa (2020) in their study showed that an increase in economic growth as well induces more of $CO_2$ emissions in most African countries. Using the Kaya identity, Ayompe et al. (2020) studied energy-related $CO_2$ emissions data of 27 African countries from 1990-2017. Results reveal an increasing trend in the emissions of $CO_2$ over the study period, with Mozambique as the highest emitter. The short and long-run impact of economic growth and energy consumption on GHG emissions was examined by Yusuf et al. (2020). $CO_2$, $CH_4$, and $N_2O$ emissions from six oil-producing African countries were used as a case study. Findings from this study showed evidence of a positive impact of economic growth on $CO_2$, $CH_4$ emissions in the long run, and on $CH_4$ emissions in the short run. On the other hand, the energy consumption had an insignificant impact on $CO_2$, $CH_4$, and $N_2O$ emissions in both the short and long run.

The effect of GHG emissions on health outcomes in Africa is studied as well. Using Nigeria as a case study, Matthew et al. (2018), and Nkalu and Edeme (2019) adopted different methodology, and both results showed that an increase in $CO_2$ emissions significantly reduces life expectancy. Several works of literature have studied GHG emissions from various sectors of some countries in Africa. For instance, sectors like agriculture (Osabohien et al., 2019; Tongwane and Moleotsi, 2018; Tsubo and Tongwane, 2017) and waste (Ngwabie et al., 2019; dos Muchangos et al., 2019; Maqhizu et al., 2019; Maria et al., 2019).

The mentioned studies and most literature have looked into the analysis of $CO_2$ emissions of some selected African countries in the light of its source of emission and their various impacts. However, few studies have focused on other anthropogenic GHG emissions. These are methane ($CH_4$), nitrous oxide ($N_2O$), and fluorinated gases. Although $CO_2$ emissions constitute most of anthropogenic GHGs emission and are the most likely cause of global warming (Chen et al., 2018), $CH_4$ has 28-36 global warming potential (GWP) times that of $CO_2$, $N_2O$ has a GWP 265-298 times that of $CO_2$, and fluorinated gases have over thousand or ten of thousands GWP (EPA, 2021). To this effect, our study focuses on these aforementioned GHG emissions with $CO_2$ emissions inclusive.
Long-term goals of achieving net-zero emission by 2050 around the world require urgent action and nationally determined contributions (UNCC, 2021). As a response, Africa is pursuing policies that will aid in minimizing its GHGs emissions as these GHGs have a long-life span of over thousands of years in the atmosphere (IPCC, 2014; EPA, 2021). However, a limitation of the efforts to mitigate GHG emissions in developing economies is the commitment of financial and technological resources (Adzawla et al., 2019). In addition, the world’s top ten poorest countries in 2020 are from Africa (Luca Ventura, 2020). Therefore, the effectiveness of policies will require understanding how these GHG emissions evolve across space and time simultaneously and the impact of the interaction of space and time on these emissions in Africa to maximize these minimal resources. To this end, this study considers spatio-temporal models fitted within the Bayesian framework to the total GHG emissions from major sectors in Africa over 27 years. Inference was based on integrated nested Laplace approximation (INLA) implemented through the R-INLA package in R.

Bayesian spatio-temporal models have proved helpful in understanding space-time dynamics of different outcomes, including infectious disease modelling (Wang et al., 2008; Raghavan et al., 2016), criminal studies (Law et al., 2014), and breastfeeding initiation and duration (Gayawan and Adjei, 2020). In particular, Hundera et al. (2020) studied the dynamics of land-use and land-cover, and its implication to GHGs in Adama District, Ethiopia, by adopting spatio-temporal analysis. The findings of our study will hopefully provide helpful information that will serve as guides to policymakers in curbing the continuous increase of these emissions in Africa.

Data

The data used for the study were obtained from the World Resource Institute (WRI), responsible for the collection and keeping of climatic data. The yearly data were on the total GHG emissions in Africa from 1990-2016, a period of 27 years. Due to the strict requirements of the spatio-temporal method adopted, an entity in the spatial component must share boundaries with one or more entities. The data on African countries sharing boundaries with at least one African country was extracted. A total of 44 countries that met the requirement were considered for this study. The total GHG emissions included in the study are CO$_2$, CH$_4$, N$_2$O, and fluorinated gases. These GHGs excluding CO$_2$ are reported in their Million metric tons of CO$_2$ equivalent (MtCO$_2$e) and summed up with CO$_2$ emissions to make the total GHG emissions for each country. These emissions are a combination of emissions from five sectors: agriculture, energy, industrial, land-use, and waste. The countries represent the spatial component, while the years serve as the temporal component for the analysis. Fig. 1 presents a ratio map of Africa, showing the countries included in the study.

Statistical analysis

Bayesian spatio-temporal modelling

Bayesian spatio-temporal models take into account the spatial effect, temporal effect, and the interaction between these two effects. Let $Y$ be the vector of natural logarithm transform of GHG emissions where $y_{ij}$ represents the natural logarithm transform of GHG emissions at location $i$ for $i = 1, 2, 3, \ldots, 44$ and time $j$ for $j = 1, 2, 3, \ldots, 27$. $y_{ij}$ is assumed to be normally distributed with mean $\mu$ and variance $\sigma^2$ and is denoted as

$$Y_{ij} \sim N(\mu, \sigma^2).$$

The mean $\mu_{ij}$ of the normal distribution can be linked to the spatial and temporal effects through a linear predictor specified as:
\[ \eta_{ij} = b_0 + u_i + s_i + \phi_j + \gamma_j + \delta_{ij}, \]

where \( b_0 \) is the intercept, \( u_i \) and \( s_i \) are the forms of spatial effect, \( \phi_j \) and \( \gamma_j \) are the forms of temporal effects, and \( \delta_{ij} \) is the spatio-temporal interaction effect.

Various models based on the subset of the full model were explored. The purpose was to determine what could be gained or lost by fitting models without spatio-temporal interactions. The complete models are described:

Model 1: \( \eta_{ij} = b_0 + s_i + \phi_j \)
Model 2: \( \eta_{ij} = b_0 + u_i + \gamma_j \)
Model 3: \( \eta_{ij} = b_0 + s_i + \gamma_j \)
Model 4: \( \eta_{ij} = b_0 + u_i + s_i + \phi_j + \gamma_j \)
Model 5: \( \eta_{ij} = b_0 + u_i + \phi_j + \delta_{ij} \)
Model 6: \( \eta_{ij} = b_0 + s_i + \phi_j + \delta_{ij} \)
Model 7: \( \eta_{ij} = b_0 + u_i + s_i + \phi_j + \gamma_j + \delta_{ij} \)
Model 8: \( \eta_{ij} = b_0 + s_i + \gamma_j + \delta_{ij} \)

The first four models do not account for spatio-temporal interaction (\( \delta_{ij} \)) while the last four models account for this. Model 1 considers the structured spatial effect (\( s_i \)) and the unstructured temporal effect (\( \phi_j \)). The unstructured spatial effect (\( u_i \)) and the structured temporal effects (\( \gamma_j \)) are considered in Model 2. Model 3 accounts for the structured spatial and structured temporal effects. Models 1 and 2 are nested in Model 4. Unstructured spatial, unstructured temporal effects and the interaction between both effects are considered in Model 5. Models 1 and 4, with the inclusion of their interaction effects, make Model 6 and 7, respectively. Model 3 with an added interaction effect makes Model 8.

Model comparison and selection was made using the Deviance Information Criterion (DIC), defined
as

\[ DIC = pD + \bar{D}, \]

where \( pD \) is the effective number of parameters, and \( \bar{D} \) is the mean deviance. The model that has the smallest DIC value is selected as the model that fits the data best.

**Prior specification**

A Bayesian approach was adopted for inference, which requires prior specifications for all model parameters. A normal prior is assigned to the unstructured spatial and temporal components that assume no dependency among the spatial units and time points. They are modeled as independent and identically distributed (iid) with the unstructured spatial effect \( u_i \) given as \( u_i \sim \mathcal{N}(0, \sigma_u^2) \), and the unstructured temporal effect \( \phi_j \) given as \( \phi_j \sim \mathcal{N}(0, \sigma_\phi^2) \).

The spatially structured effects are assigned a conditional autoregressive (CAR) prior distribution that accounts for the boundary shared among countries (i.e. neighbours) and is given as

\[ s_i | s_j, i \neq j \sim \mathcal{N}\left( \frac{1}{N(i)} \sum_{j=1}^{n} s_j, \frac{\sigma^2}{N(i)} \right), \]

where \( s_j \) are neighbors of \( s_i \), \( \sigma^2 \) is the variance, and \( N(i) \) is the number of the neighbors of \( i \).

A second-order random walk is assigned as a prior to the structured temporal effect to account for the temporal autocorrelation and is given as

\[ y_t | y_{t-1}, y_{t-2} \sim \mathcal{N}(2y_{t-1} + y_{t-2}, \sigma^2), \]

where \( y_t \) is the observation at current time \( t \), \( y_{t-1}, y_{t-2} \) are observations at previous time, and \( \sigma^2 \) is the variance.

The Bayesian computation was done using the Integrated Nested Laplace Approximation (INLA) [Blangiardo and Cameletti (2015)] to obtain posterior estimates of the model parameters.

**Results**

Fig. 2 presents the temporal trend of the log-transformed GHGs emissions for each country across the 27 years. It can be observed that all countries have positive trends, except that of three countries, Gabon, Kenya, and Rwanda, that experienced a fall in the GHGs emissions at some time. While an increasing trend of GHGs emissions over the years is observed for Algeria, Cameroun, Chad, Egypt, Ethiopia, Guinea, Mali, Morocco, Niger, Tunisia, and Tanzania, fluctuations in the GHGs emissions of the remaining countries are noticed over the years. Countries that constitute the top emitters of GHGs throughout the 27 years period are South Africa, Nigeria, Egypt, Zambia, Democratic Republic of Congo (DRC), and Cameroun.

Table 1 shows the model diagnostic statistics for the seven models fitted to the dataset. Models 2-4 without spatio-temporal interactions have similar DIC values and outperform Model 1 that considers the unstructured temporal effect and structured spatial effect. This implies that the model performs better when the temporal effect is structured or a combination of both structured and unstructured than when only the unstructured temporal effect is accounted for. Models 5-8, on the other hand, reveals the importance of capturing the spatio-temporal interactions within spatio-temporal models as they all outperform Models 1-4 except for Model 6. Results presented in Fig. 3 and Fig. 4 are based on Model 7 with the least DIC value. The intercept of Model 7 has an estimated mean of 3.6392 with a 95% credible interval (CI) of [3.6225, 3.6558]. This implies that the average total GHGs emission from the 44 African countries is estimated to be 38.0614 MtCO\(_2\)e and is statistically significant since its 95% CI does not include zero.
Fig. 2. Temporal trend plot of the log of the GHGs emissions for the 44 African countries.

Fig. 3 presents the structured temporal pattern for GHGs emissions. The upper and lower black lines in the temporal plot represent the 95% credible intervals (CI), while the blue line represents the posterior mean. The closeness of the CI to the mean estimate indicates a small standard deviation of the estimates. The plot reveals that the GHG emissions over time have a pattern similar to a sinusoidal pattern. An increase in GHGs emissions is visible between 1990 and 1998, immediately
Table 1: Model diagnostic statistics. S = Spatial, T = Temporal, u = unstructured, s = structured, and int = interaction

| Models | Model Description | DIC (D) | pD  |
|--------|-------------------|---------|-----|
| 1      | S (s) + T (u)     | 2185.37 | 2140.35 | 45.02 |
| 2      | S (u) + T (s)     | 2173.21 | 2125.40 | 47.81 |
| 3      | S (s) + T (s)     | 2173.33 | 2125.53 | 47.80 |
| 4      | S (u+s) + T (u+s) | 2173.71 | 2126.67 | 47.04 |
| 5      | S (u) + T (u) + int | 1842.42 | 1178.93 | 663.49 |
| 6      | S (s) + T (u) + int | 2193.42 | 2116.87 | 76.55 |
| 7      | S (u+s) + T (u+s) + int | 148.80  | -353.87 | 502.67 |
| 8      | S (s) + T (s) + int | 152.09  | -349.55 | 501.64 |

followed by a decline from 1999 to 2003. The estimated GHGs emissions picked up again in 2003, with a continuous increase until 2008. Little or no change in the estimated GHGs emissions between 2008 and 2010 is seen, followed by a slight reduction in GHGs emissions from 2010 to 2012. Since then, an increase in GHGs emissions is evident up to the year 2016.

Fig. 3. Structured Temporal trend showing the posterior mean with 95% CI of the GHGs emissions

Fig. 4 shows the effect of the interaction of space and time on the total GHGs emissions from each country. It is observed that from 1990-2016, the estimates of the total GHGs emissions of Nigeria, DRC, Angola, Zambia, Tanzania, and South Africa were among the top emissions. On the other hand, the GHGs emissions estimate of Cameroun, Egypt, Sudan, Algeria, and Ethiopia, are among the top emissions in 1993, 1996, 2002, 2007, and 2008 respectively. The countries maintained this category until 2016, except for Sudan that fell out of the category between 2013 to 2015 and later bounced back in 2016. Countries with the least estimates of GHGs emissions in Africa over the study period are Mauritania, Gabon, Equatorial Guinea, Rwanda, Eritrea, Guinea-Bissau, Sierra-Leone, Burundi, and Djibouti. Interestingly, there was a drastic reduction in GHGs emissions from Kenya between the years 2000-2006, but there has been an increase afterward. Generally, the total GHGs emissions in
Africa are increasing steadily within each country, with more countries having a high tendency to join the train of top emitters over time.

Fig. 4. Spatio-temporal plot of the posterior mean of the GHGs emissions with spatially structured and temporally structured interaction.
Discussions and conclusion

The increased emission of greenhouse gases has been a major concern across the globe. The importance of studying the behavior of GHGs emissions cannot be overlooked because they contribute to global warming and global warming, contributing to climate change. This study analyzed the patterns in the emissions of GHGs employing Bayesian spatio-temporal approach that considered space and time effects and the interaction between these two entities.

Different forms of spatial and temporal effects were considered in the spatio-temporal models developed in the study. Interestingly, models that accounted for the spatio-temporal interactions outperformed the models that did not account for these interactions. These interactions often provide useful and helpful information in situations where temporal trends vary spatially, and the omission of these interactions in spatio-temporal models may lead to loss of such useful information (Anderson and Ryan 2017). Some study results on spatio-temporal modelling as well have shown that models with spatio-temporal interaction terms performed better than simpler models (Wang et al. 2008; Law et al. 2014). Our study findings reveal that the model that accounts for the structured spatial effect, structured temporal effect, and the interaction between these two effects best fit the dataset. This implies that spatial correlation and temporal correlation exist in GHG emissions from Africa across the 27 years. This may be a result of the long lifespan of these GHGs in the atmosphere. According to IPCC, the life-span of CO₂ in the atmosphere is between 5 to 200 years while the life-span of CH₄, N₂O, SF₆, PFCs, and HFCs in the atmosphere are 12, 114, 3200, 50000, and 270 years, respectively.

Spatio-temporal plots were obtained due to the structured spatial effect, structured temporal effect, and spatio-temporal interaction effects considered in the model. The structured effects in the model accounted for the boundaries shared among countries. The plots revealed the impact of the boundary shared among countries on the evolution of GHGs emissions over a long period compared to a short period. Countries that are likely to have high estimates of GHG emissions throughout the study period affected the emissions of some of their neighbouring countries, particularly those that are likely to have lower estimates of GHG emissions. Some of these neighbouring countries later experienced an increase in their emissions, with some eventually having high estimates over a long period. For instance, Algeria, Egypt, and Nigeria maintained high estimates of GHG emissions over the study period. An increase in the emissions of some of their neighbouring countries such as Mali, Morocco, Niger, and Tunisia for Algeria, Cameroun, Chad, and Niger for Nigeria, and Sudan for Egypt became evident over the period. Countries that shared boundaries with these neighbouring countries also experienced an increase in their emissions after some while. For instance, an increase in emission was evident in Ethiopia and Burkina Faso, with both countries sharing boundaries with Sudan and Mali. From these findings, a collective effort among African countries is vital in reducing GHG emissions and achieving net-zero emissions, particularly among countries that share a boundary.

Furthermore, countries such as Angola, Cameroun, Democratic Republic of Congo, Nigeria, South-Africa, Tanzania, and Zambia with high estimates of GHG emission in 1990 maintained this category all through the study period. These may indicate that policies and strategies laid down in these countries to reduce and mitigate GHG emissions may not be effective enough. Therefore, these countries may need to have a re-look at the policies and probably restrategize. The majority of the GHG emissions in Zambia are traced to be from the land-use change and forestry sector, with the country being listed among those with the highest deforestation rate coupled with a projected increase in this rate (USAID 2011). South Africa is the highest emitter of GHGs in Africa, with most of the emissions of South Africa and Angola emanating from the energy sector (USAID 2019). Nigeria, on the other hand, is ranked the second-highest emitter of GHG after South Africa with a higher percentage of the GHG emissions of Nigeria, DRC, Tanzania, and Cameroun traced to land-use change and forestry sector (USAID 2019). The evolution of the GHG emissions across space and time as revealed in the findings indicates that more African countries have high estimates of GHG emissions over time, with
the hot-spot countries being Nigeria, DRC, Angola, Zambia, Tanzania, South Africa, Egypt, Ethiopia, Cameroun, Sudan, and Algeria. Though Africa contributes the least to global emissions, our findings show that these emissions in Africa are rapidly increasing, with more countries likely to have high GHG emissions. Individual countries in Africa have laid out plans of mitigating and reducing GHG emissions in their respective countries. For instance, South Africa, the top 20 global emitter and top Africa emitter has launched a mitigating measure called South Africa’s Low Emission Development Strategy (SA-LEDS) with a focus on the sectors contributing to the emissions [Katie Capp, 2019].

In conclusion, given that reduction in GHGs emissions is vital for tackling global warming and climate change, the findings from this study can provide insight and helpful information for policymakers in mitigating and controlling GHG emissions in African countries. The spatio-temporal map has identified the impact of boundaries shared among countries on the amount of GHGs emitted over the years. Therefore, the collective efforts from countries in controlling the increase of GHG emissions in Africa will be more effective. Also, the countries that are likely to emit high GHGs are revealed in the spatio-temporal map. These countries can perhaps adopt strategies employed by countries with a low likelihood of high GHG emissions throughout the study period. Since the GHG emissions used for this study are an aggregate from the main sectors in African countries, further work can be done. For instance, a Bayesian spatio-temporal analysis of these emissions can be conducted on individual sectors such as agriculture, waste, land-use change and forestry, energy, and industry. This can help identify the various sectors that are likely to contribute most to these emissions from each African country. In addition, factors such as population size and gross domestic product can be included as covariates in the spatio-temporal models thus, providing additional explanations for the model’s result.

Declarations

Funding
No funding was received to conduct this study and preparation of this manuscript

Conflict of interest
The authors declare no conflicts of interest

Availability of data
The data used for this study was obtained from The World Resource Institute at https://datasets.wri.org/dataset/cait-country

Code availability
Not available

Authors’ contributions
Gayawan conceived and designed the study, critical revision of the manuscript. Akeresola conducted the data analysis, interpreted the results and drafted the manuscript.

Ethics approval
Not applicable

Consent to participate
Not applicable
Consent for publication
Not applicable

References

Adzawla, W., Sawaneh, M., and Yusuf, A. M. (2019). Greenhouse gasses emission and economic growth nexus of sub-saharan africa. *Scientific African*, 3.

Anderson, C. and Ryan, L. (2017). A comparison of spatio-temporal disease mapping approaches including an application to ischaemic heart disease in new south wales, australia. *International Journal of Environmental Research and Public Health*, (2).

Ayompe, L. M., Davis, S. J., and Egoh, B. N. (2020). Trends and drivers of african fossil fuel CO₂ emissions 1990–2017. *Environmental Research Letters*, 15(12):124039.

Bewket, W. (2012). Climate change perceptions and adaptive responses of smallholder farmers in Central Highlands of Ethiopia. *International Journal of Environmental Studies*, 3(69):507–523.

Blangiardo, M. and Cameletti, M. (2015). *Spatial and Spatio-temporal Bayesian models with R-INLA*. John Wiley & Sons.

Bruckner, T., Bashmakov, I., Muhugetta, Y., Chum, H., de la Vega Navarro, A., Edmonds, J., Faaij, A., Fungtammasan, B., Garg, A., Hertwich, E., Honnery, D., Infield, D., Kainuma, M., Khennas, S., Kim, S., Nimir, H., Riahi, K., Strachan, N., Wiser, R., and Zhang, X. (2014). Energy Systems. In: *Climate Change 2014: Mitigation of Climate Change*. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Carter, I. (2007). Footsteps.Climate change and agriculture. *Tearfund, UK*, pages 1–4.

Chen, J., Wang, P., Cui, L., Huang, S., and Song, M. (2018). Decomposition and decoupling analysis of CO₂ emissions in oecd. *Applied Energy*, 231:937–950.

Darghouth, M. and Bouattour, A. (2008). Ticks and tick-borne diseases of livestock in North Africa, present state and potential changes in the context of global warming. *Livestock and Global Climate Change*.

dos Muchangos, L. S., Tokai, A., and Hanashima, A. (2019). Greenhouse gas emissions and cost assessments of municipal solid waste treatment and final disposal in Maputo City. *Environment, Development, and Sustainability*, 21(1):145–163.

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Kadner, S., Minx, J., Brunner, S., Agrawala, S., and Baiocchi, G., e. a. (2014). Technical summary. In: *Climate Change 2014: Mitigation of Climate Change*. IPCC Working Group III Contribution to AR5.

EPA (2021). United States Environmental Protection Agency. Greenhouse gas emissions: Understanding global warming potentials. [https://www.epa.gov/ghgemissions/understanding-global-warming-potentials](https://www.epa.gov/ghgemissions/understanding-global-warming-potentials). Accessed: 29 April 2021.

Gayawan, E. and Adjei, C. (2020). Bayesian spatio-temporal analysis of breastfeeding practices in ghana. *GeoJournal*.

Hundera, H., Mpandeli, S., and Bantider, A. (2020). Spatiotemporal Analysis of Land-use and Land-cover Dynamics of Adama District, Ethiopia and Its Implication to Greenhouse Gas Emissions. *Integrated Environmental Assessment and Management*, 16(1):90–102.
IPCC (2014). Summary for policymakers. In: Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate. Cambridge University Press, Cambridge, UK and New York, USA.

Katie Capp (2019). Announcing the USAID South Africa Low Emissions Development Program on Climatelinks. https://www.climatelinks.org/blog/announcing-usaid-south-africa-low-emissions-development-program-climatelinks. Accessed: 29 June 2021.

Koneswaran, G. and Nierenberg, D. (2008). Global farm animal production and global warming: impacting and mitigating climate change. Environmental health perspectives, 116(5).

Law, J., Quick, M., and Chan, P. (2014). Bayesian spatio-temporal modeling for analysing local patterns of crime over time at the small-area level. Journal of Quantitative Criminology, (1):57–78.

Leila, R. (2013). Climate change impacts on north african countries and on some tunisian economic sectors. Journal of Agriculture and Environment for International Development, 107.

Leimbach, M., Roming, N., Schultes, A., and Schwerhoff, G. (2018). Long-term development perspectives of sub-saharan africa under climate policies. Ecological Economics, 144:148–159.

Lelieveld, J., Klingmüller, K., Pozzer, A., Burnett, R. T., Haines, A., and Ramanathan, V. (2019). Effects of fossil fuel and total anthropogenic emission removal on public health and climate. Proceedings of the National Academy of Sciences, 116(15):7192–7197.

Luca Ventura (2020). Global Finance News: Poorest Countries in the World 2020. https://www.gfmag.com/global-data/economic-data/the-poorest-countries-in-the-world Accessed: 29 April 2021.

Maqhuzu, A. B., Yoshikawa, K., and Takahashi, F. (2019). The effect of coal alternative fuel from municipal solid wastes employing hydrothermal carbonization on atmospheric pollutant emissions in Zimbabwe. Science of The Total Environment, 668:743–759.

Maria, C., Góis, J., and Leitão, A. (2019). Challenges and perspectives of greenhouse gas emissions from municipal solid waste management in Angola. Energy Reports.

Matthew, O., Osabohien, R., Faniyi, F., and Fasina, A. (2018). Greenhouse gas emissions and health outcomes in Nigeria: Empirical insight from auto-regressive distribution lag technique. International Journal of Energy Economics and Policy, 8:43–50.

Ngaira, J. (2007). Impact of climate change on agriculture in Africa by 2030. Scientific Research and Essays, 2:238–243.

Ngwabie, N. M., Wirlen, Y. L., Yinda, G. S., and VanderZaag, A. C. (2019). Quantifying greenhouse gas emissions from municipal solid waste dumpsites in Cameroon. Waste Management, 87:947–953.

Niang, I., Ruppel, O. C., AbdRabo, M. A., Essel, A., Lennard, C., Padgham, J., and Urquhart, P. (2015). Africa Climate Change 2014: Impacts, Adaptation and Vulnerability: Part B: Regional Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Nkalu, C. N. and Edeme, R. K. (2019). Environmental hazards and life expectancy in Africa: evidence from GARCH model. SAGE Open, 9(1).
Olubusoye, O. E. and Musa, D. (2020). Carbon emissions and economic growth in Africa: Are they related? *Cogent Economics & Finance*, 8(1):1850400.

Osabohien, R., Matthew, O., Aderounmu, B., and Olawande, T. I. (2019). Greenhouse gas emissions and crop production in West Africa: Examining the mitigating potential of social protection. *International Journal of Energy Economics and Policy*, 9(1):57–66.

Ragavan, R., Goodin, D., Neises, D., Anderson, G., and Ganta, R. (2016). Hierarchical Bayesian Spatio-Temporal Analysis of Climatic and Socio-Economic Determinants of Rocky Mountain Spotted Fever. *PloS One*, 11(3).

Shobande, O. A. (2020). The effects of energy use on infant mortality rates in Africa. *Environmental and Sustainability Indicators*, 5:100015.

Siti, A. (2014). Carbon Dioxide Emission in the Middle East and North African (MENA) Region: A Dynamic Panel Data Study. *Journal of Emerging Economies and Islamic Research*, (3).

Stocker, T. (2013). *Climate change 2013 the physical science basis: Working Group I contribution to the fifth assessment report of the intergovernmental panel on climate change*.

Stott, P., Tett, S., Jones, G., Allen, M., Mitchell, J., and Jenkins, G. (2000). External control of 20th century temperature by natural anthropogenic forcing. *Science*, 290:2133–2137.

Tongwane, M. and Moeletsi, M. (2018). A review of greenhouse gas emissions from the agricultural sector in Africa. *Agricultural Systems*, 166:124–134.

Tsubo, M. and Moeletsi, M. and Tongwane, M. (2017). Enteric methane emissions estimate for livestock in south Africa for 1990–2014. *Atmosphere*, 8(5).

Umar, B., Alam, M., and Al-Amin, A. (2021). Exploring the contribution of energy price to carbon emissions in African countries. *Environmental Science and Pollution Research*, 28:1973–1982.

UNCC (2021). United Nation Climate Change News: Countries in Asia, the Middle East and North Africa Are Ready to Step up Climate Action. [https://unfccc.int/news/countries-in-asia-the-middle-east-and-north-africa-are-ready-to-step-up-climate-action](https://unfccc.int/news/countries-in-asia-the-middle-east-and-north-africa-are-ready-to-step-up-climate-action). Accessed: 28 April 2021.

USAID (2011). United States Agency International Development. Greenhouse Gas Emissions in East Africa.

USAID (2019). United States Agency International Development. Greenhouse Gas Emissions in West Africa.

van der Zwaan, B., Kober, T., Longa, F., van der Laan, A., and Jan Kramer, G. (2018). An integrated assessment of pathways for low-carbon development in Africa. *Energy Policy*, 117:387–395.

Vastag, B. (2009). The melting snows of Kilimanjaro. *Nature*.

Wang, X. H., Zhou, X. N., Vounatsou, P., Chen, Z., Utzinger, J., Yang, K., Steinmann, P., and Wu, X. (2008). Bayesian Spatio-temporal modeling of Schistosoma japonicum prevalence data in the absence of a diagnostic 'gold' standard. *PLoS Neglected Tropical Diseases*, 2(6).

Xu, Z., Sheffield, P., Hu, W., Su, H., Yu, W., Qi, X., and Tong, S. (2012). Climate change and children’s health—a call for research on what works to protect children. *International Journal of Environmental Research and Public Health*, 9(9):3298–3316.

Yusuf, A. M., Abubakar, A. B., and Mamman, S. O. (2020). Relationship between greenhouse gas emission, energy consumption, and economic growth: evidence from some selected oil-producing African countries. *Environmental Science and Pollution Research*, pages 1–9.