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The drivers of GHG emissions: A novel approach to estimate emissions using nonparametric analysis

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ABSTRACT

The rising levels of global GHG emissions underpin climate change, hence, taking an appropriate inventory of the drivers and patterns of anthropogenic emissions remains crucial to mitigating global climate effects. However, there are conflicting views in the literature on the relationship between respective drivers and GHG emissions due to the lack of robust analysis that accommodates the interaction of all significant drivers. We use novel estimation techniques to decipher the 26-year inventory of GHG occurrences and simultaneous assessment of interactions in 50 countries stratified based on socioeconomic developments over the period 1990–2018. This study highlights different drivers of GHG emissions under broader categories such as population, economic development, forest density, and agricultural practices. Non-parametric estimations roughly confirm the magnitude of the influence of forests, agriculture, and land-use intensity on GHG emissions, ultimately tracking the most significant emission sinks.

1. Introduction

Human needs for goods and services are indefinite, while the Earth only provides finite resources for humans to exploit. This situation creates an imbalance between demand and supply, especially amid the continuously rising population and the shortening availability of land to produce raw materials. During the last decade, the world's population has increased by 12 %, from 6,922 billion in 2010 to 7,753 billion in 2020. This growing population supplies more labour to the global economy, which in turn drove the global Gross Domestic Product (GDP) by 38 %, from US$ 66,163 trillion in 2010 to US$ 84,705 trillion in 2020. However, this high growth ironically occurs at the cost of declining forest areas and higher carbon emissions. The World Bank estimated that global forest density, in terms of the percentage of land area, has diminished from 31 % in 2006 to 30.71 % in 2016. Furthermore, carbon emission has also increased from 4,277 metrics ton per capita in 2009 to 4,484 metric tons per capita in 2018 (World Development Indicators data). This condition calls for attention from scholars and policymakers about reducing Greenhouse Gas (GHG) emissions across the globe.

Due to its global adverse impact, combating GHG has become a top priority for the United Nations, and its importance is manifested through the 2030 Agenda of Sustainable Development Goals (SDGs). Adopted in 2015 and signed by 193 UN member countries, the widely known "2030 Agenda" targets affordable and clean energy as one of the channels to achieve its ultimate goal of ending global poverty. Specifically, SDG-7 comprises specific targets on

Abbreviations: AFOLU, Agriculture, Forestry, and Other Land Uses; CH_4, Methane; CO_2, Carbon dioxide; EKC, Environmental Kuznets Curve; FMOLS, Fully Modified Ordinary Least Squares; GDP, Gross Domestic Product; GHG, Greenhouse Gas; LLC, Land Carrying Capacity; MENA, Middle East and North Africa; ML, Machine Learning; N_2O, Nitrous Oxide; RMSE, Root Mean Square Error; SDGs, Sustainable Development Goals; SSA, Sub-Saharan African; WB, World Bank; WDI, World Development Indicators.

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clean energy, recommends universal access to affordable, reliable, and modern energy services (7.1), and increases the share of renewables in the global energy mix (7.2) (Chopra et al., 2022).

Some recommendations for achieving the SDGs were expressed by scholars. For example, according to Chen et al. (2021), the best way to achieve sustainable growth and decent work (SDG-8) is to increase transparency in the financial framework using technological processes. Furthermore, industrial actors can lower their pollution by promoting the use of advanced technologies that support clean and affordable energy (SDG-7). In addition, Sinha et al. (2020) proposed that nations that have achieved SGD-7 should be motivated to pursue a sustainable environment (SGD-13). Thus, the transition from fossil-based energy to energy-efficient technology can be realized through innovations that decrease environmental deterioration, create green employment, and improve environmental quality. Also, it is essential to determine Land Carrying Capacity (LCC) to ensure the safety of ecosystems and their sustainable development, or at least to slow down the degradation of natural capital (Magazzino and Santeramo, 2023; Ojekemi et al., 2023).

One other popular channel in combating GHG is through population control, economic growth, and land density. The relationship between population, economic growth, forest density, and GHG emissions (i.e., carbon emissions) has been studied extensively. However, there are at least two research gaps existing in the previous literature. First, most studies investigated the nexus partially, meaning that no study exactly investigated the impact of these three variables – population, economic growth, and forest density, simultaneously, on GHG. For example, Bu et al. (2022), Rehman and Rehman (2022), Hong et al. (2022), and Alaganthiran and Anaba (2022), among others, only focused on the relationship between population and GHG, without considering economic growth or land density. On the other hand, Champeecharoensuk et al. (2022), Magazzino and Falcone (2022), Oladunni et al. (2022), and Kais and Sami (2016) only focused on the relationship between economic growth and carbon emissions without considering population growth or land density. Finally, other studies comprising Rossi et al. (2023), Yang et al. (2023), Shen et al. (2022), Noojipady et al. (2017), among others, only focused on the impact of forest density – including arable land use or cropland – on carbon emissions, without incorporating the role of economic growth or population.

Second, in terms of the impact of population on GHG, different studies produce different conclusions. For example, in terms of the nexus between population and carbon emissions, some studies demonstrated that a higher population induces more GHG emissions (Rehman and Rehman, 2022; Oladunni et al., 2022). However, other studies found that population does not necessarily increase carbon emissions (Hong et al., 2022; Bu et al., 2022). Likewise, Cui et al. (2019) argued that the impact of population on GHG emissions follows a U-shaped relationship where the rise in population is initially followed by carbon emission reduction, but the impact becomes severe after surpassing a certain threshold. On the contrary, other studies report that the impact of the population on carbon emissions is negative, meaning that the rising population can reduce GHG emissions due to higher economies of scale (Liu et al., 2021). Daramola et al. (2021) demonstrate that the link between population and carbon emissions is bidirectional and higher carbon emissions have a negative impact on population size.

Third, in the context of the relationship between economic growth and environmental degradation, a debate is also persistent, particularly in terms of the presence of the Environmental Kuznets Curve (EKC) hypothesis. Some studies demonstrated that the impact of economic growth on carbon emissions follows an inverted U-curve. This implies that rising economic growth initially increases emissions until it reaches an extreme point before the impact diminishes gradually (Oladunni et al., 2022; Kais and Sami, 2016). This argument is based on the assumption that higher economic growth will encourage the development of technology and innovation to tackle the carbon issue. Kostakis et al. (2023) found that economic growth increases carbon emissions and follows the EKC hypothesis in MENA countries. In contrast, other studies argue that the impact of economic growth on carbon emissions does not follow the EKC hypothesis. For example, Mikayilov et al. (2017) demonstrated that economic growth induces more carbon emissions with no sign of a turning point as per the EKC hypothesis. Contrarily, Magazzino (2016) found that carbon emission has a negative impact on economic growth.

Finally, in terms of the relationship between forest density and carbon emissions, there are several existing studies with mixed findings in assessing the role of deforestation on carbon emissions. On one side, some studies demonstrate the detrimental impact of deforestation on the environment. For instance, Yang et al. (2023) showed that deforestation is the largest source of carbon emissions. The study is conducted in China over the period of 1700–1980 using a bookkeeping model. Furthermore, Shen et al. (2022) found that land use intensification significantly reduces methane (CH_4) emissions but increases nitrous oxide (N_2O) emissions. Thus, the impact of land use on environmental degradation depends on the specific detailed land use. On the contrary, Rossi et al. (2023), who evaluated the temporal variability of soil carbon emissions and its relationship with related variables such as the carbon dioxide (CO_2) flux model, demonstrate that soil carbon emission tends to be lower for high-density land use and higher for native forests.

Given the highlighted research gaps, this paper contributes to the ongoing debate by pioneering the simultaneous assessment of the interaction among population, economic growth, forest density, and GHG emissions from a global perspective. In fact, our research integrates 50 countries with different levels of economic development covering low-income, lower-middle, upper-middle, and high-income economies. Some research objectives are the following. We can show that aside from understanding the nexus, we further explore the topic more deeply by deciphering the 28-year inventory of GHG occurrences and simultaneously assessing the interaction between GHG emission and the key drivers in countries stratified based on socioeconomic developments. Contrary to previous literature, our contributions include: first, a sample of 10 low-income, 18 lower-middle-income, 12 upper-middle-income, and 10 high-income economies over the period from 1990 to 2018, which is the level of sample diversity not explored intensively by the literature in the same area. This large and diverse sample can provide a new perspective on the impact of forests, agriculture, composite variable, population, and economic growth on total GHG emissions at a global scale within multiple socioeconomic developments. Second, this study highlights various drivers of GHG emissions under broader categories such as population, economic development, forest density, and agricultural practices. Thus, we use a comprehensive indicator for assessing climate change where GHG emissions are proxied by carbon dioxide, methane, nitrous oxide, and fluorinated gases emissions, while land-use intensity is proxied by the log of a composite measure of agricultural land (i.e., arable, permanent pastures, and cropland) and forest area. Third, we evaluate the nexus using a novel estimation technique by employing Lasso regression and partially nonparametric regression in a panel data context, a technique that, to the best of our knowledge, has not been implemented on this topic. Lasso regression is utilized to identify the most predictive lag structure for the covariates included in the model. Once the best linear specification to predict the dependent variable is found, the partially nonparametric regression is applied to the identified specification. Through this procedure, we can identify the contribution of each driver to the total GHG emissions by partialling out the effect of other drivers. GHG emissions depend on a complex interplay among social, physical, and chemical factors, whose dynamic cannot be entirely captured by traditional linear modelling. The joint use of a Machine Learning (ML) approach (Lasso) and of a partially nonparametric (or semi-parametric) approach provides ground for a more accurate estimation of the relationship between GHG emissions and their drivers. In different settings, previous papers used nonparametric methods to model the relationship between GHG emissions and their drivers (Krüger and Tarach, 2022; Magazzino et al., 2021; Wang and Feng, 2021; Azomahou et al., 2006). Our paper is however the first to use a semiparametric regression jointly with an ML optimal specification method.

This paper delivers three model specifications, namely (1) the effect of urban population on total GHG emissions, (2) the effect of economic development on GHG emissions, and (3) the effect of forest density on total GHG emissions. Some findings from the paper stand out. First, we demonstrate that population growth has a significant impact on GHG emission outgrowth. Specifically, the increase in population size significantly corresponds to higher GHG emissions. Second, based on the second model, we observe a significant and negative impact of economic growth on GHG emissions. This infers that higher economic development corresponds to mitigating GHG emission intensity. Third, forest density has a positive and significant effect on GHG emissions, implying that more deforestation activities trigger more global anthropogenic GHG emissions. Overall, the population has the greatest magnitude of impact on GHG emissions, while the impact magnitude of forest density is similar to that of economic growth.

This paper is organized as follows: Section 2 presents the literature review. Section 3 provides the materials and methods, whereas Section 4 describes the regression methodologies. Section 5 gives a discussion of the empirical findings, while Section 6 concludes with policy directions.

2. Literature review

There is rising scholarly attention on the nexus among emissions, population, economic growth, and land density. The role of population and its related series, including population growth, population size, or urbanization rate on carbon emissions has been studied through the lens of different methodologies (Magazzino and Cerulli, 2019). Theoretically, a higher population growth corresponds to higher energy demands; notwithstanding, findings from studies investigating its impact on emissions remain inconsistent. Bu et al. (2022) investigated the impact of population on energy consumption and carbon emission in China. The sample covered 30 provinces during the period 2000–2019 using population migration as a proxy for population. The results demonstrate that population migration increases energy consumption in terms of natural gas and coal consumption, without increasing carbon emissions. Furthermore, the study also shows that population migration raises energy poverty in the form of gaps among provinces in terms of their access to energy. Hong et al. (2022) inspected the impact of urban population and urban density on carbon emissions in China. The results highlight that increasing urban density has a positive impact on environmental quality and thus reduces carbon emissions when the urban population is smaller than one million. Otherwise, if the urban population is beyond this threshold, urban density exerts a detrimental effect on environmental quality.

Rehman and Rehman (2022) explored the impact of population growth and urbanization on energy consumption, carbon emissions, and economic development in the five most populated countries in Asia (China, Indonesia, Pakistan, India, and Bangladesh) from 2001 to 2004. The study shows that the nexus among population growth, urbanization, emissions, and economic development is mixed. In fact, the study found that population growth and economic development are two major causes of emissions in India, while the major contribution of carbon emissions in Pakistan and China is urbanization and energy consumption, respectively. The study also provides a possible causal relationship between unsustainable population growth and environmental degradation at a regional level. Alaganthiran and Anaba (2022) analyzed the key drivers of carbon dioxide emissions in 20 Sub-Saharan African (SSA) countries from 2000 to 2020. Some key drivers include per capita GDP, international tourist arrivals, energy use, and urban population. Based on panel data regression analysis, the study demonstrates that international tourist arrival and energy use – particularly fossil fuel – drive carbon emissions in the region. These findings are also similar to those by Daramola et al. (2021), who also investigated the relationship between population growth and carbon emissions in African countries, showing that population growth shares a negative relationship with carbon emissions.

Using data on eastern, central, and western regions of mainland China over the period 2000–2016, Cui et al. (2019) argued that the impact of population size on carbon emissions is not linear. Instead, a U-shaped relationship emerges, where the negative impact of population size becomes substantial after a certain level of emissions. The research applied panel threshold regression with carbon dioxide (CO_2) emissions per unit of electricity production as a dependent variable, while urban population was approximated by the year-end total population in districts or cities. The study found that urban population size and carbon emissions have a U-shaped relationship. This implies that at the level before the extreme point, the rise in population size inhibits carbon emissions before it becomes detrimental once the population size exceeds the threshold level. In that case, rising population size can induce higher carbon emissions. Based on a study conducted using the Magna cum oil-producing African countries over the period of 2000–2019, Daramola et al. (2021) explained the possibility of a backward relationship between changes in population growth and carbon emissions. Thus, the study revealed a significant negative effect of carbon emissions on population growth. In contrast, other papers clarify that aside from population size, the flow of population from rural to urban areas affects carbon emissions. The increasing standard of living in urban areas explains why urbanization appears as a link through which population growth leads to higher energy demands, thus intensifying carbon emissions. Wang et al. (2014) and Zhang and Lin (2012) state that urbanization and carbon emissions are positively associated. Even more, Wang et al. (2014) found that the two variables constituted a long-run relationship with a bi-directional positive causality. In addition, the strength of the association in China varies across regions. These findings on the positive association between urbanization and carbon emissions confirm the theory presented by Jones (1991), asserting that urbanization permits higher economies of scale in production, due to more demand for transportation and food, which inevitably increases energy consumption.

On the contrary, other studies establish that due to economies of scale, higher population size correlates with lower carbon emissions. This relationship is mostly found for cities. Dodman (2009) showed that cities refer to higher economies of scale that can drive technological innovation to reduce carbon pollution. For China, Liu et al. (2021) demonstrated that, although a higher population size encourages carbon emissions, it surprisingly curbs emissions per capita in 175 cities. However, this argument contradicts Fragkias et al. (2013), who investigated the impact of population size on carbon emissions using cities in the US covering 366 metropolitan statistical areas and 576 micropolitan areas. The study demonstrates that higher-populated cities are slightly more efficient than less-populated cities. As such, they do not solidify the presence of economies of scale in large cities compared to smaller cities.

Oladunni et al. (2022) examined the factors affecting environmental degradation emissions in 9 provinces in South Africa during the period of 2011–2020. The environmental degradation is approximated using GHG emissions, while the key drivers include economic growth, energy intensity, national population, infrastructural investments, freight turnover, fuel consumption, and passenger vehicles. The findings highlight that economic growth, population, and energy intensity represent the major drivers of GHG emissions in this region. Using decomposition analysis, Alajmi (2021) demonstrated that industrial activity and real energy intensity – particularly electricity production and petroleum processing – is a major determinant of carbon emissions in Saudi Arabia. However, applied studies on the topic of pollution determinants always incorporate various economic variables as controls. Among others, economic growth (i.e., usually approximated by GDP) is mostly the dominant variable included in the estimated model. Recently, the impact of economic growth on the environment has gained attention as global warming is becoming a serious issue (Kais and Sami, 2016). Therefore, most environmental studies take into account economic growth either as a focused independent variable or as a control. The general finding on the relationship between economic growth and emissions underpins the EKC hypothesis (where the relationship follows an inverted U-shaped relationship), which is indicated by the presence of an extreme point. This peak reflects a structural and technological change resulting from high economic growth, which in turn curbs long-term emission intensity. However, the inverted U-shaped relationship between economic growth and emissions is evident in some studies (Magazzino et al., 2023).

Using the cross-sectional dependence test, Granger causality, and panel data estimators, Kostakis et al. (2023) showed that economic growth is positively correlated with carbon emissions while validating the EKC hypothesis in MENA countries. Champeecharoensuk et al. (2022) investigated the impact of economic development on environmental degradation in Thailand from 2007 to 2020. The study shows that transportation contributes to environmental degradation in the country, even though with a small impact. Kais and Sami (2016) applied dynamic panel data analysis (GMM System) for the years 1990–2012, finding that economic growth and per capita carbon emissions create an inverted U-shaped relationship, confirming the EKC hypothesis across 48 countries in 3 macro-areas (European and North Asian, Latin American and Caribbean, and Middle East and North Africa countries). On the contrary, multiple studies invalidate the presence of the EKC in the selected sample. Mikayilov et al. (2018) investigated the relationship between economic growth and carbon emissions in Azerbaijan between 1992 and 2013. The study shows that economic growth increases long-run emissions, confirming the absence of the EKC hypothesis. This finding also resonates with that of Mikayilov et al. (2017), who argued that a higher population induces more carbon emissions due to greater use of transportation.

Among studies in the area of carbon emissions, little attention is being paid to the nexus of GHG emissions and land, which is mostly cultivated for agricultural purposes such as arable land and cropland. Land use has been widely considered a local cause of environmental degradation (Foley, 2005), given that human exploitation of land has been expanding due to the increasing demand. Several studies in this literature ascertain how land use stimulates carbon emissions. In Brazil, land use, land conversion, and forestry accounted for two-thirds of Brazil's GHG emissions in 2005 (Noojipady et al., 2017). In the UK, the production and supply of food contribute to 20–30 % of GHG emissions (Kulak et al., 2013). Spawn et al. (2019) found that cropland expansion increases carbon emissions in the US. However, a global study that examined the inducing impact of land use on emissions argues that croplands do not contribute to production intensity (i.e., GHG emissions) across countries (Carlson et al., 2016). Shen et al. (2022) inspected the impact of land use intensification on environmental degradation in China (Taihu Lake region). The study approximates environmental degradation using CH_4 and N_2O emissions, demonstrating that land use intensification significantly reduces CH_4 emissions but increases N_2O emissions. Thus, the impact of land use on environmental degradation depends on the specific land use. That is, converting natural wetlands to rice-wealth rotation fields can enhance the greenhouse effect, although it weakens the greenhouse effect when the land is converted from rice-wealth rotation fields to greenhouse vegetable fields. Yang et al. (2023) estimated the size of carbon emissions in China using a bookkeeping model. The study provides evidence that deforestation is the largest carbon emission source. More specifically, over 70 % of carbon emissions were caused by harvesting wood, while less than 30 % were caused by converting forest and grassland to cropland. Rossi et al. (2023) evaluated the temporal variability of soil carbon emissions and its relationship with related variables such as the CO_2 flux model, enhanced vegetation index, gross primary productivity, leaf area index, soil moisture, and soil CO_2. The results highlight that soil carbon emission tends to be lower for high-density land use and higher for native forests.

In summary, there is no consensus in the existing literature that examines the impact of population, economic growth, and land on emissions. Many studies show mixed findings on the nexus of these three variables, indicating a sensitivity issue in terms of sample and methodology selection. Across the literature we have assessed, there are some research gaps that exist in the previous literature.

3. Materials and methods

3.1. Data

The global sample includes 50 countries across all development levels from 1990 to 2018. The 50 countries selected are based on data availability and comprise 10 low-income economies, 18 lower-middle-income economies, 12 upper-middle-income economies, and 10 high-income economies. All the variables utilized in the model are derived from the World Development Indicators (WDI), a World Bank (WB) database. The total GHG emissions (kt of CO_2 equivalent) represent the dependent variable, whereas the independent variables in each model include urban population, economic growth, and land-use intensity. Contrary to previous attempts, we use a comprehensive indicator for assessing climate change, viz. GHG emissions comprise carbon dioxide, methane, nitrous oxide, and fluorinated gases. The population is proxied by the log of population size, economic growth is approximated by the log of GDP, and land-use intensity is proxied by the log of a composite measure of agricultural land (i.e., arable, permanent pastures, and cropland) and forest area. Based on methodologies and guidelines of the indicators of sustainable development, land-use intensity, a composite variable is calculated as ((Agric*weight of Agric) + (Forest*weight of forest))/2, where the weight of Agric is defined as Agric divided by the sum of Agric and forest, and weight of forest is defined as forest divided by sum of Agric and forest (Sarkodie and Owusu, 2022). All the variables in the model are presented in terms of the natural logarithm.

3.2. Model estimation

In this study, we jointly use optimal model specification through the Lasso method, and a partially nonparametric regression for GHG emissions. The use of a model embedded in the larger family of nonparametric regression models has several advantages over traditional parametric regression models (Henderson and Parmeter, 2015; Li and Racine, 2007; Pagan and Ullah, 1999):

Flexibility: nonparametric regression methods are more flexible in terms of the shape of the relationship between the predictors and response variables. Unlike parametric models, nonparametric methods do not require strong assumptions about the functional form of the relationship.
Robustness: nonparametric regression models are generally more robust to outliers and other data anomalies than parametric models. Since nonparametric methods are not based on specific assumptions about the data distribution, they can handle a wider range of data distributions, thus making results more transparent.
Data-driven: nonparametric methods are data-driven, which means they are designed to adapt to the data rather than trying to force the data to fit a specific model. This makes nonparametric methods more suitable for complex and nonlinear relationships.
Interpretation: nonparametric regression models can provide more interpretable results than parametric models in certain cases. For example, kernel regression methods can produce smoothed estimates of the data distribution, which can be useful in visualizing the relationship between the predictor and response variables.
Scalability: Nonparametric methods can be used to analyze large datasets with many predictors and observations. Many nonparametric regression methods are computationally efficient and can handle large datasets with ease.

Overall, nonparametric regression methods are a powerful tool for analyzing complex data relationships as the ones considered in this study and can provide more flexible and robust models than traditional parametric regression methods.

We estimate a partially nonparametric autoregressive equation in a panel data context. The underlying regression for N cross-sectional units observed over T periods is modelled as follows:

$$y_{i,t} = \alpha_i + \lambda_t + m(z_{i,t}) + \sum_{k=1}^{K}\gamma_k y_{i,t-k} + \sum_{k=1}^{K}\delta_k z_{i,t-k} + \sum_{k=1}^{K}\beta_{1k}x_{1i,t-k} + \sum_{k=1}^{K}\beta_{2k}x_{2i,t-k} + \varepsilon_{i,t} \quad (1)$$

where $i = 1,\ldots,N$ and $t = 1,\ldots,T$; α_i captures the country effect; λ_t the time effect; γ_k the autoregressive endogenous parameters; β_{1k} and β_{2k} the exogenous autoregressive parameters of the variables x_1 and x_2, respectively; δ_k the exogenous autoregressive parameters of the variable z; $m(z_{i,t})$ is the function linking $y_{i,t}$ to $z_{i,t}$ in an unknown way; and $\varepsilon_{i,t}$ is a pure error shock with zero mean and finite variance. The main goal of our analysis is to estimate $m(\cdot)$ conditional on the country and time fixed effects and the autoregressive components of the dependent and independent variables. We also assume that $k = 3$, to account for at most a three-year autoregressive process (Cerulli, 2015).

In Eq. (1), the first problem is to identify the structure of the autoregressive components. Indeed, we do not want to leave in the model all the $k = 3$ components, as only a subset of them should matter for predicting the outcome. We thus run a Lasso regression of Eq. (1) by dropping out $m(z_{i,t})$. The Lasso is an ML feature-selector linear method allowing us to select the sole autoregressive components that have high predictive power on our outcome excluding all those with poor predictive power. This makes us able to obtain a more parsimonious model producing an optimal predicting balance between bias and variance. By stacking the set of Lasso selected regressors in the column vector $w_{i,t}$ also containing the fixed effects, Eq. (1) becomes:

$$y_{i,t} = m(z_{i,t}) + \pi w_{i,t} + \varepsilon_{i,t} \quad (2)$$

where π collects the parameters of the predictors selected by the Lasso. Eq. (2) is a partially linear (or partially nonparametric) regression that can be consistently estimated by the so-called "double partialling out" method provided in Robinson (1988). This procedure allows for nonparametrically estimating the unknown function $m(z_{i,t})$ obtaining at the same time a root-N consistent estimate of π. The "double partialling out" procedure goes as follows:

Step 1. Take the expectation of Eq. (2) conditional on $z_{i,t}$, thus obtaining:

$$E(y_{i,t}|z_{i,t}) = m(z_{i,t}) + \pi E(w_{i,t}|z_{i,t}) \quad (3)$$

Step 2. Subtract Eq. (3) to Eq. (1) obtaining:

$$\left[y_{i,t} - E\left(y_{i,t}|z_{i,t}\right)\right] = \pi[w_{i,t} - E(w_{i,t}|z_{i,t})] + \varepsilon_{i,t} \quad (4)$$

Step 3. Estimate nonparametrically (for instance, by a kernel polynomial regression) the two conditional expectations $E(y_{i,t}|z_{i,t})$ and $E(w_{i,t}|z_{i,t})$, compute the two residuals $\hat{r}_{y,it}$ and $\hat{r}_{w,it}$, and estimate consistently π by a Least Squares (LS) regression of $\hat{r}_{y,it}$ on $\hat{r}_{w,it}$.

Step 4. Once obtained $\hat{\pi}$ by the previous step, we can use Eq. (2) and obtain:

$$Y_{i,t} = m(z_{i,t}) + \varepsilon_{i,t} \quad (5)$$

where $Y_{i,t} = y_{i,t} - \hat{\pi} w_{i,t}$ is the partialled-out $y_{i,t}$. In Eq. (5), we can estimate $m(z_{i,t})$ with any possible non-parametric method. In this application, a univariate kernel local linear approach is performed, as it shares good asymptotic properties together with reasonable computational costs.

Once we have an estimate of $m(z_{i,t})$, we can plot it as a function of $z_{i,t}$. Moreover, we can compute the partial effect of $z_{i,t}$ on $Y_{i,t}$, that is:

$$\frac{\partial E\left(Y_{i,t}|z_{i,t}\right)}{\partial z_{i,t}} = m\prime(z_{i,t}) \quad (6)$$

The expectation of this function over the support of $z_{i,t}$ will provide us with the APE of $z_{i,t}$ on $Y_{i,t}$:

$$APE_{z\rightarrow Y} = \frac{\partial E\left(Y_{i,t}|z_{i,t}\right)}{\partial z_{i,t}} = E_z[m(z_{i,t})] \quad (7)$$

This is a singleton number synthesizing the overall effect of $z_{i,t}$ on $Y_{i,t}$. Standard Errors and P-Values are obtained via bootstrapping technique.

4. Empirical results

By carrying out three times the previous procedure, we estimated $m(z_{i,t})$ and $m'(z_{i,t})$ assuming $z_{i,t}$ to be equal to the log of *PO* (urban population), log of GDP (gross domestic product), and log *COMP* (composite measures of arable, permanent pastures, cropland, and forest). In this way, we can identify the contribution of each driver $z_{i,t}$ to the *EM* (total GHG emissions), by partialling out the effect of the other drivers. The log transformation allows to account for data heteroskedasticity and presents parameters in the form of elasticities.

4.1. The effect of forests on GHG emissions

We start by estimating Eq. (1) via a Lasso regression to identify the most predictive lag structure for the covariates included in the model (Table 1). In this case, we use 10-fold cross-validation over 92 variables and 1,269 observations. The optimal tuning of the model is obtained at a lambda of 0.0012 at which 81 out of 92 predictors are selected, mostly dummy variables related to country and year fixed effects. Once we found the best linear specification able to predict the log of *EM*, we run Eq. (2) over this specification to then estimate *m(z)* and *m'(x)*.

Table 2 presents the results of the linear component of Eq. (2), where the two lags of *FOR* are not statistically significant; However, it is evident the significant effect of the second lag of *EM* with a negative sign, and a size smaller than one (remember that the coefficients should be interpreted as elasticities). *PO* stands out with a positive and significant elasticity of 1.29, indicating an increasing return of CO_2 emissions to this variable. Also, the lags of *PO* have positive and significant effects, but with small elasticities. GDP has weak mixed effects, mainly with a negative sign. The adjusted *R*-squared is 0.68 (with an RMSE = 0.7366), which is sizable.

Table 3 shows the results of the nonparametric estimation of *m(z)* and *m'(z)*, the core of our study. This aims to measure non-parametrically the effect of *FOR* on *EM*. We immediately see that the effect is highly significant with a positive elasticity of 0.39 meaning that, when *FOR* increases by 10 %, *EM* increases by 3.9 %. It is a sizable effect, but lower than one, thus signaling low decreasing returns of *EM* to *FOR*. The *R*-squared is rather high as well, around 54 %.

Fig. 1a plots the *m(z)* function. The curvature of this function shows non-linearity. We first have a decrease in the log of EM until around 11 when the log of FOR is around 1.9; after this point, there is a steeper increase in the log of EM until a level of 15; this part is probably responsible for an average positive effect. The observations' cloud is rather concentrated, thus making this result enough robust.

An advantage of running a semi-parametric model is the opportunity to analyze and visualize the distribution of the effect, i.e. the empirical distribution of *m'(z)*. This distribution is visible in Fig. 1b. We see that all observations show an elasticity smaller than one, thus signalling decreasing returns of *EM* to *FOR*. A large mass of observations is also concentered between 0.2 and 0.6, proving that the relationship between these two variables is sufficiently strong.

Then, Fig. 1c shows the distribution of the prediction of *m(z)*. This distribution is a bit right-skewed around the mean that, as shown in Table 3, is equal to 12.50. The range of variation is rather large; thus, we can conclude that the predictions of *EM* to different levels of *FOR* are rather heterogeneous.

4.2. The effect of agriculture on GHG emissions

As shown in Table 4, in this case, we use 10-fold cross-validation over 92 variables and 1,269 observations. The optimal tuning of the model is obtained at a lambda of 0.00139 at which 82 out of 92 predictors are selected, mostly dummy variables related to country and year fixed effects.

Table 5 sets out the results of the linear component of equation (2), where it is evident the significant effect of the first and second lag of the log of *EM*, with a negative sign, and a small size in both cases smaller than one. Also, in this case, the role played by the variable *PO* stands out, with a highly significant elasticity of 1.27. The adjusted *R*-squared is 0.68 (with an RMSE = 0.7343), which is a good size.

Table 6 aims to non-parametrically measure the effect of *AGRIC* on *EM*: this effect is poorly significant with a negative elasticity of −0.09: so, if *AGRIC* increases by 10 %, *EM* decreases by less than 1 %. It is a tiny effect. The *R*-squared is also rather small, around 18 %.

Fig. 2a plots the *m(z)* function. The curvature of this function is not linear. After the value of circa 2.5 of the log of *AGRIC*, we can first observe a decrease in *EM*, until a value of *AGRIC* around 3.5; after this point, there is a sustained increase in the log of *EM*. The observations' cloud is rather scattered, thus making this result characterized by some degree of uncertainty.

From Fig. 2b one can notice that all observations show a negative elasticity smaller than one, thus signalling negative decreasing returns of *EM* to *AGRIC*. A large mass of observations is also concen-

Table 2
Partially nonparametric regression results: Effect of *FOR* on *EM*.

Variable	Coefficient
EM_{t-1}	−0.0151 (0.0274)
EM_{t-2}	−0.1117*** (0.0302)
EM_{t-3}	0.0250 (0.0293)
GDP_t	−0.0786 (0.0500)
PO_t	1.2868*** (0.1357)
$AGRIC_t$	−0.1029 (0.0673)
GDP_{t-1}	−0.1452*** (0.0470)
GDP_{t-2}	−0.1473*** (0.0520)
GDP_{t-3}	0.0462 (0.0443)
PO_{t-2}	0.2668** (0.1238)
PO_{t-3}	0.2659* (0.1495)
$AGRIC_{t-1}$	−0.0824 (0.0658)
$AGRIC_{t-2}$	−0.1033 (0.0666)
$AGRIC_{t-3}$	0.0225 (0.0632)
FOR_{t-1}	−0.0533 (0.0944)
FOR_{t-2}	−0.0166 (0.1202)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3
Non-parametric estimation of the effects of *FOR* on *EM*.

	Observed estimate
Mean	12.5018*** (0.0258)
Effect	0.3875*** (0.0274)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

Table 1
Lasso regression results: effect of *FOR* on *EM*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	0.9164	1	0.1058	1.7474
71	lambda before	0.0014	80	0.6918	0.6023
72 *	selected lambda	0.0013	81	0.6919	0.6021
73	lambda after	0.0011	80	0.6919	0.6021
88	last lambda	0.0003	90	0.6915	0.6028

Notes: * lambda selected by cross-validation.

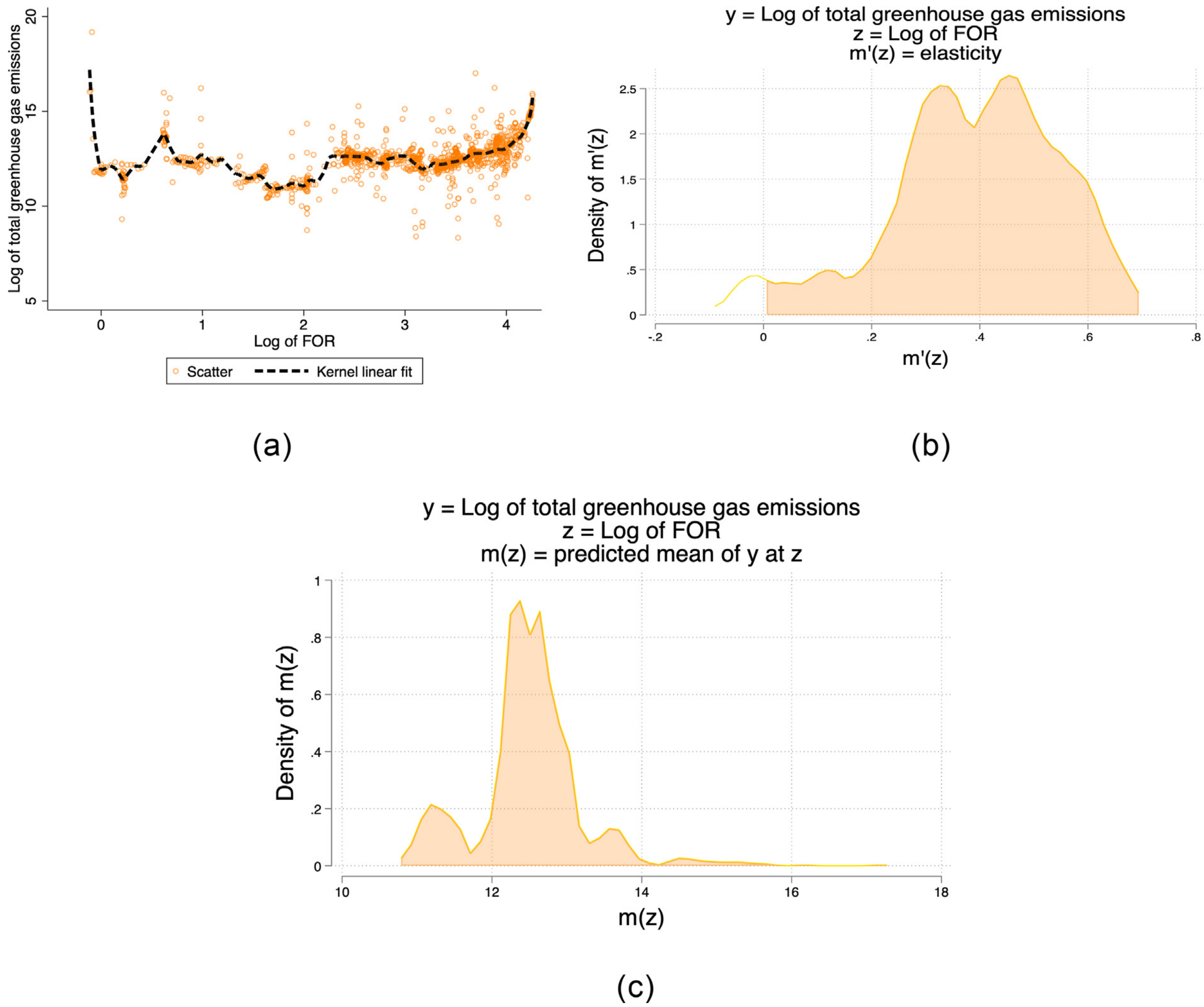

Fig. 1. The effect of forest on GHG emissions. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 4
Lasso regression results: effect of *AGRIC* on *EM*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	1.0286	1	0.0096	1.9354
71	lambda before	0.0015	82	0.6896	0.6065
72 *	selected lambda	0.0014	82	0.6897	0.6063
73	lambda after	0.0013	79	0.6897	0.6063
79	last lambda	0.0007	86	0.6891	0.6076

Notes: * lambda selected by cross-validation.

tered between −0.10 and −0.05, proving that the relationship between these two variables is negative and not particularly strong.

Fig. 2c shows the distribution of the prediction of *m(z)*. This distribution is rightward skewed around the mean (12.50). The range of variation is rather large, so that the predictions of *EM* to different levels of *AGRIC* are rather heterogeneous.

4.3. The effect of a composite variable on GHG emissions

The results in Table 7 show that we use 10-fold cross-validation over 88 variables and 1,269 observations. The optimal tuning of the model is obtained at a lambda of 0.00258 at which 76 out of 88 predictors are selected, mostly dummy variables related to country and year fixed effects.

Table 8 sets out the results of the linear component, where it is evident the significant and positive effect of *PO* with an elasticity of 89.9 %. In addition, the second lag of *PO* has a strong effect with an elasticity value of 24 %. The other variables have mixed-in-sign and smaller effects. The adjusted *R*-squared is 0.68 (with an RMSE = 0.7403), which is of a rather high size.

From Table 9 it emerges that the effect of *COMP* on *EM* is highly significant with a high positive elasticity of 0.71 meaning that, when *COMP* increases by 10 %, *EM* increases by 7.1 %. It is a remarkable effect. The *R*-squared is however rather small, around 12 %.

Fig. 3a plots the *m(z)* function: its curvature is not linear. After the value of around 2 for *COMP*, we can first observe a decrease in

Table 5
Partially nonparametric regression results: Effect of *AGRIC* on *EM*.

Variable	Coefficient
EM_{t-1}	−0.0813*** (0.0278)
EM_{t-2}	−0.0862*** (0.0294)
EM_{t-3}	0.0239 (0.0286)
GDP_t	−0.0416 (0.0528)
PO_t	1.2664*** (0.1086)
FOR_t	0.2240 (0.1484)
GDP_{t-1}	−0.1533*** (0.0497)
GDP_{t-2}	−0.1224** (0.0543)
GDP_{t-3}	0.0317 (0.0440)
PO_{t-2}	0.4223** (0.0773)
PO_{t-3}	0.1364 (0.1154)
$AGRIC_{t-1}$	−0.0618 (0.0612)
$AGRIC_{t-2}$	−0.0515 (0.0657)
$AGRIC_{t-3}$	0.0910 (0.0666)
FOR_{t-1}	−0.2788*** (0.0921)
FOR_{t-2}	−0.0674 (0.0870)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6
Non-parametric estimation of the effects of *AGRIC* on *EM*.

	Observed estimate
Mean	12.4966*** (0.0213)
Effect	−0.0879* (0.0464)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

EM, until a value of *COMP* around 2.5; after this point, there is a sustained increase in *EM*. The observations' cloud is rather concentrated, thus making this result characterized by a good degree of reliability.

The empirical distribution of *m'(z)* is given in Fig. 3b. All observations show a positive elasticity smaller than (but close to) one, thus signalling soft decreasing returns of *EM* to *COMP*. A large mass of observations is also concentered between 0.6 and 0.8, proving that the relationship between these two variables is positive and particularly strong.

Fig. 3c shows the distribution of the prediction of *m(z)*. This distribution shows four peaks, but the variance around the mean – equal to 12.49 as shown in Table 9 – is not strong. So, we conclude that the predictions of *EM* to different levels of *COMP* are sufficiently homogenous.

4.4. The effect of GHG emissions on forest

Using 10-fold cross-validation over 88 variables and 1,269 observations, the optimal tuning of the model is obtained at a lambda of 0.00062 at which 80 out of 88 predictors are selected, mostly dummy variables related to country and year fixed effects (see Table 10).

Having found the best linear specification able to predict the log of *FOR*, we present in Table 11 the results of the linear component of Eq. (2): the first lag of *EM* is highly significant (at a 1 %); while the effect of the second and third lag of *GDP* is statistically significant. The adjusted *R*-squared is 0.97 (with an RMSE = 0.1676), which is definitely high.

In Table 12 we report the non-parametrically effect of *EM* on *FOR*, which is not significant and very small, with a negative sign. The *R*-squared is also small, around 20 %.

Fig. 4a plots the *m(z)* function. The curvature of this function is very flat, indicating no substantial effect of *EM* on *FOR*.

The empirical distribution of *m'(z)* is left-skewed; it could be noticed that around half of the observations show a negative elasticity, and the other half a positive one, although all elasticities are rather small. This signals no effect of *EM* towards *FOR* (Fig. 4b).

Regarding the distribution of the prediction of *m(z)*, it is right-skewed around the mean (=2.88). The range of variation is rather large, so the predictions of *FOR* to different levels of *EM* are rather heterogeneous.

4.5. The effect of GHG emissions on agriculture

We use 10-fold cross-validation over 88 variables and 1,269 observations. The optimal tuning of the model is obtained at a lambda of 0.00023 at which 86 out of 88 predictors are selected, mostly dummy variables related to country and year fixed effects (Table 13).

In Table 14 the results of the linear component are reported: it clearly emerges the significant and strong effect of the autoregressive components of *AGRIC*. The effect of the other variables is smaller and mixed in sign. The adjusted *R*-squared is 0.70 (with an RMSE = 0.3180), which is of a very good size.

Table 15 shows that the non-parametric effect of *EM* on *AGRIC* is not significant. The *R*-squared is also rather small, around 8 %.

Fig. 5a shows that the curvature of the *m(z)* function is flat, indicating no substantial effect of *EM* on *AGRIC*. The empirical distribution of *m'(z)* is visible in Fig. 5b; only a few observations exhibit a positive elasticity, which is however very small, thus indicating again the absence of any relevant effect of *EM* to *AGRIC*. The distribution of the prediction of *m(z)* is rather symmetric around the mean (=3.71). The range of variation is rather small: the predictions of *AGRIC* to different levels of *EM* are rather homogenous (Fig. 5c).

4.6. The effect of GHG emissions on a composite variable

A 10-fold cross-validation over 88 variables and 1,269 observations is used. The optimal tuning of the model is obtained at a lambda of 0.00244 at which 55 out of 88 predictors are selected, mostly dummy variables related to country and year fixed effects (Table 16).

The estimates of *m(z)* and *m'(x)* in Table 17 evidence a statistically significant effect of the first lag of *PO* with an elasticity of 0.048, and the contemporaneous value of *PO* (elasticity of 0.038). *GDP* and *EM* are also highly significant, but with ambiguous signs. The adjusted *R*-squared is 0.65 (with an RMSE = 0.2110).

The nonparametric estimations of *m(z)* and *m'(z)* reported in Table 18 show that this effect of *EM* on *COMP* is statistically significant, but very small with a positive elasticity of −0.01. The *R*-squared is also rather small (around 6 %).

The *m(z)* function in Fig. 6a clarifies that the curvature of this function is flat, without any substantial effect of *EM* on *COMP*. In Fig. 6b the empirical distribution of *m'(z)* is depicted. Here, all observations show a positive elasticity but are very small, thus signalling no effect of *EM* on *COMP*. A small mass of observations is also concentred on negative values. The distribution of the prediction of *m(z)* is left-skewed around the mean (equal to 3.10). The range of variation is rather large, so the predictions of *COMP* to different levels of *EM* are rather heterogeneous (Fig. 6c).

To sum up all our parametric findings, we have detected:

- a unidirectional link running from GHG emissions to forestry;
- a unidirectional link running from GHG emissions to agriculture;
- a unidirectional link running from GHG emissions to a composite variable.

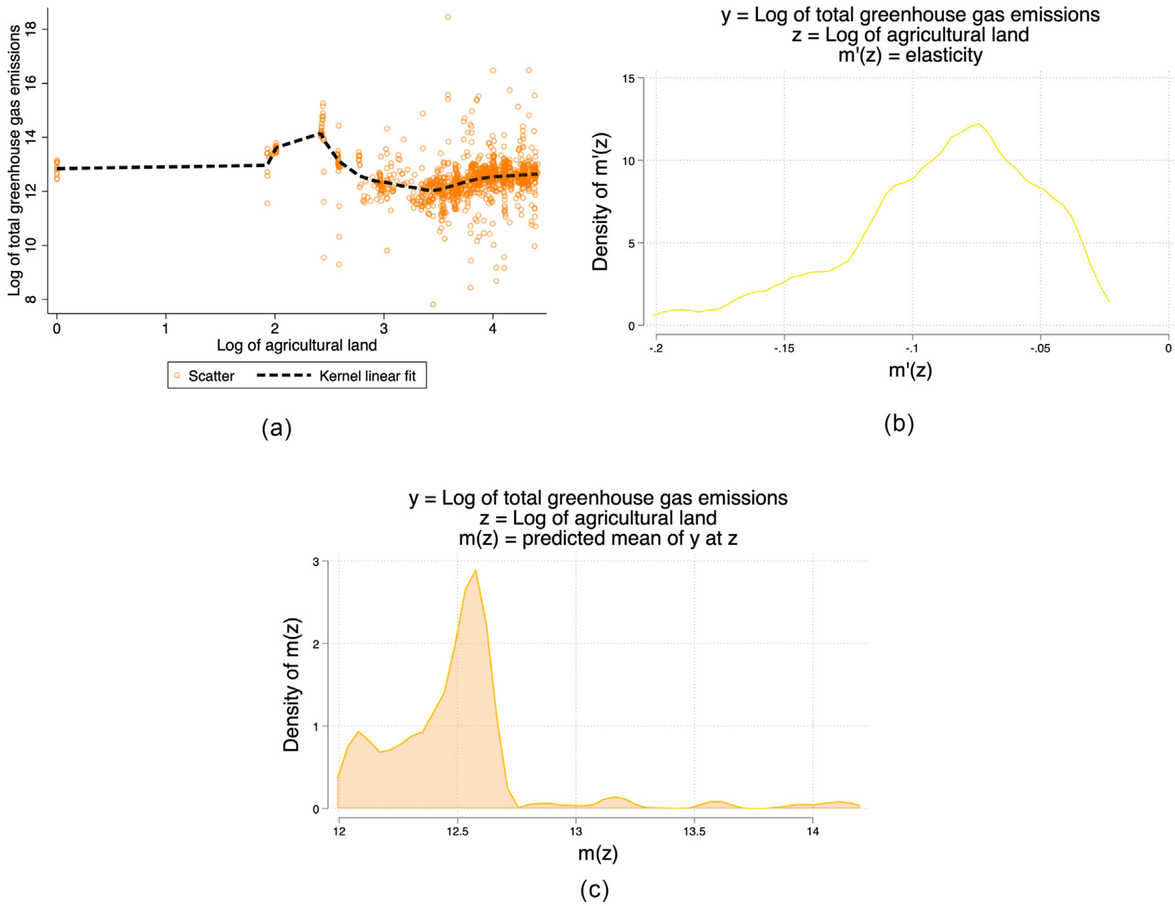

Fig. 2. The effect of agriculture on GHG emissions. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 7
Lasso regression results: effect of *COMP* on *EM*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	0.9958	1	0.0180	1.9190
64	lambda before	0.0028	76	0.6920	0.6018
65 *	selected lambda	0.0026	76	0.6921	0.6016
66	lambda after	0.0024	77	0.6919	0.6020
69	last lambda	0.0018	81	0.6913	0.6031

Notes: * lambda selected by cross-validation.

Table 8
Partially nonparametric regression results: Effect of *COMP* on *EM*.

Variable	Coefficient
EM_{t-1}	−0.0732*** (0.0273)
EM_{t-2}	−0.0830*** (0.0291)
EM_{t-3}	0.0483* (0.0279)
PO_t	0.8991*** (0.0535)
GDP_{t-1}	−0.1147*** (0.0428)
GDP_{t-2}	−0.1058** (0.0484)
GDP_{t-3}	0.1004*** (0.0376)
PO_{t-2}	0.2402*** (0.0629)
$COMP_{t-1}$	−0.1411 (0.0995)
$COMP_{t-2}$	−0.0103 (0.1040)
$COMP_{t-3}$	0.1102 (0.0975)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9
Non-parametric estimation of the effects of *COMP* on *EM*.

	Observed estimate
Mean	12.4936*** (0.0199)
Effect	0.7110*** (0.0712)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

Thus, it clearly emerges from the parametric estimates––empirical support for the hypothesis that environmental pollution has a non-negligible impact on land use variables. However, the non-parametric approach highlights a completely different story, since we discovered a significant effect of forestry on GHG emissions, agriculture on GHG emissions, and a bi-directional link between GHG emissions and a composite variable. To compare our novel estimations to traditional causality analyses, we also present in Table 19 the results of pairwise Granger causality tests. The results evidence a very different scenario; in fact, they confirm that for-

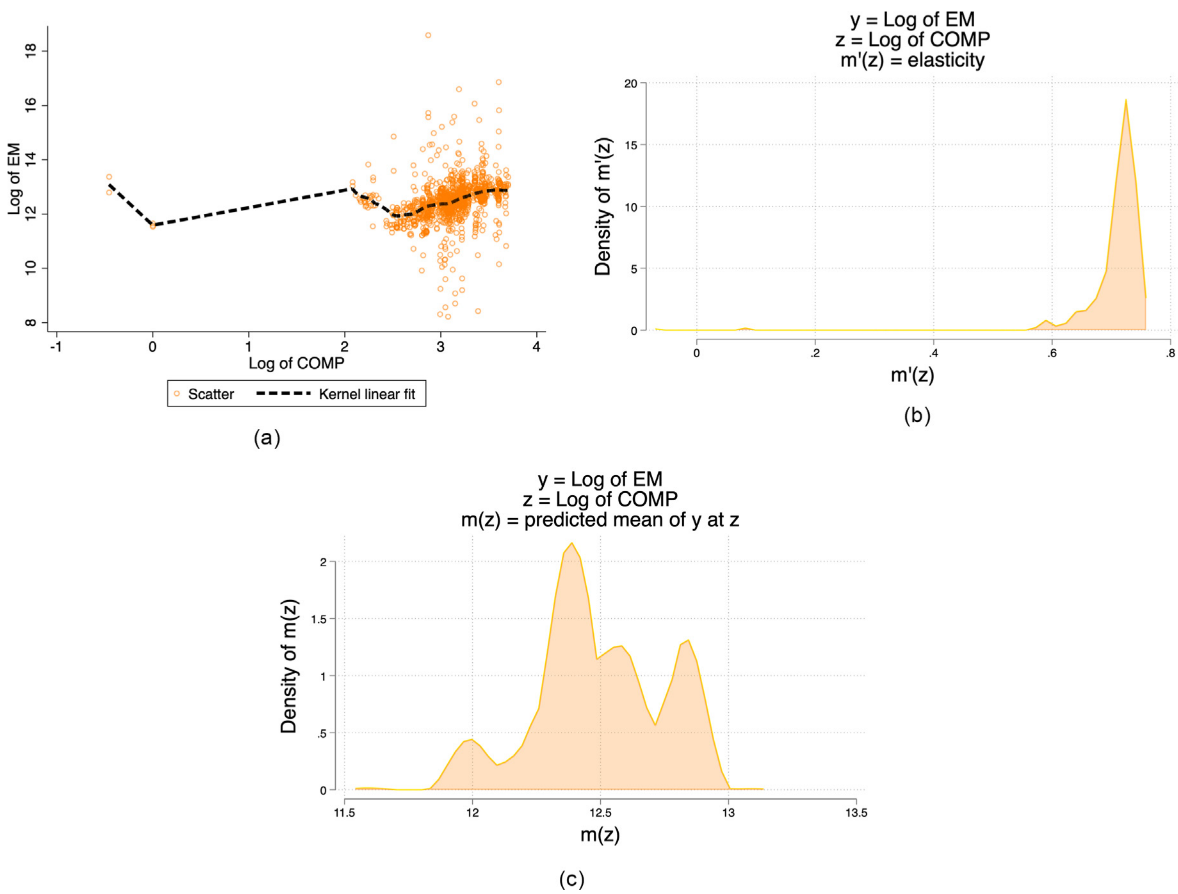

Fig. 3. The effect of a composite variable on GHG emissions. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 10
Lasso regression results: effect of *EM* on *FOR*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	0.3862	1	0.1013	1.0381
69	lambda before	0.0007	78	0.9789	0.0243
70 *	selected lambda	0.0006	80	0.9789	0.0243
71	lambda after	0.0006	80	0.9789	0.0243
76	last lambda	0.0004	79	0.9789	0.0244

Notes: * lambda selected by cross-validation.

Table 11
Partially nonparametric regression results: Effect of *EM* on *FOR*.

Variable	Coefficient
FOR_{t-1}	0.0111 (0.0312)
FOR_{t-2}	0.0218 (0.0305)
PO_t	−0.0104 (0.0283)
GDP_{t-1}	−0.0082 (0.0118)
GDP_{t-2}	0.0454*** (0.0119)
GDP_{t-3}	0.0193* (0.0102)
EM_{t-1}	−0.0171*** (0.0062)
EM_{t-2}	−0.0094 (0.0067)
EM_{t-3}	−0.0114* (0.0065)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 12
Non-parametric estimation of the effects of *EM* on *FOR*.

	Observed estimate
Mean	2.8767*** (0.0049)
Effect	−0.0017 (0.0052)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

estry does not affect GHG emissions ($F = 0.16$). However, here the absence of a statistically significant causal flow emerges for both the forestry-emissions nexus and the agriculture-emissions one. Moreover, a unidirectional causal link, running from the composite variable to GHG emissions is detected ($F = 4.01$).

5. Discussion

The end goal of the 2015 Paris Agreement is to limit the global temperature to 1.5 °C. Yet, recent trends in emissions, planned

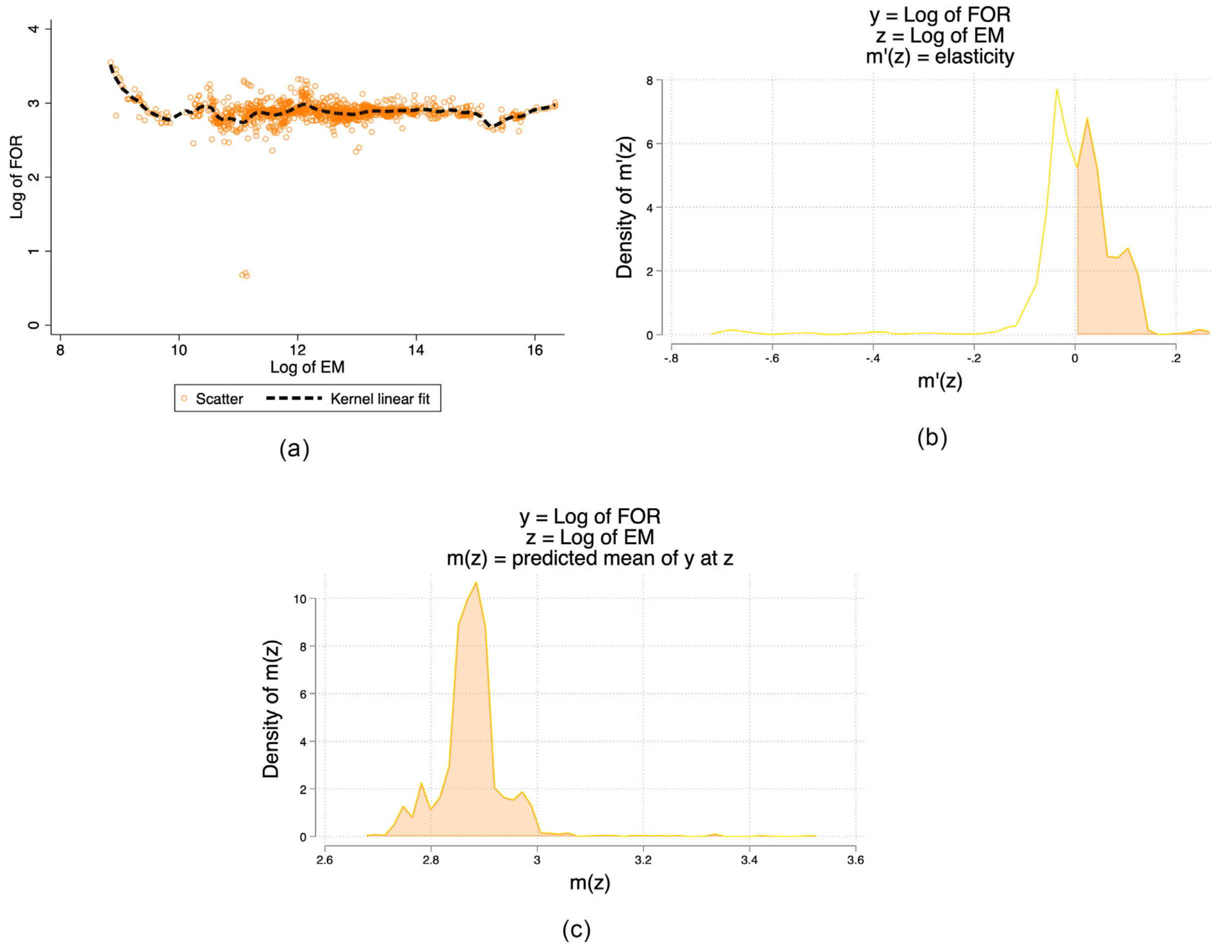

Fig. 4. The effect of GHG emissions on forest. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 13
Lasso regression results: effect of *EM* on *AGRIC*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	0.2467	1	0.0053	0.3918
75	lambda before	0.0003	86	0.7111	0.1138
76 *	selected lambda	0.0002	86	0.7111	0.1138
77	lambda after	0.0002	86	0.7111	0.1138
87	last lambda	0.0000	86	0.7108	0.1139

Notes: * lambda selected by cross-validation.

infrastructure, and national policy commitments jeopardize the likelihood of realizing these ambitious targets (Höhne et al., 2020). Although rising GHG emissions underpin accelerated global warming and climate change, taking an appropriate inventory of the drivers and patterns of GHG emissions continues to be a global challenge. There are diverse drivers of GHG emissions that are intricately intertwined and also span across several spheres of interactions between the earth and human systems. The Intergovernmental Panel on Climate Change (IPCC) Working Group III (WG3) ascribed the major global drivers of GHG emissions to five broad sectors, namely: energy systems, industry, buildings, transport, and AFOLU (Agriculture, Forestry, and Other Land Uses). In congruence with the scope of this study, a large number of such drivers were designated under broader categories such as population, economic development, forest density, and agricultural practices, amongst other anthropocentric activities. Notwithstanding, each category is characterized by labyrinthian dynamics, which pose challenges with regard to climate change mitigation. Moreover, apart from the conflicting views of scholars, lobbyists, and policymakers regarding the relationship between respective drivers and GHG emissions, we observed the lack of robust analysis in order to accommodate the interaction of all significant drivers argued in previous reports (Yang et al., 2023; Hong et al., 2022; Shen et al., 2022; Daramola et al., 2021). In this regard, we employed simultaneous assessment of interactions using novel estimation techniques to intelligently decipher the 28-year inventory of GHG (comprising CO_2, CH_4, N_2O, and fluorinated gases) emission occurrences in 50 countries stratified based on their respective socioeconomic developments. To this end, Lasso and non-parametric regression were applied successively to know the magnitude of influence each driver has on GHG emissions, thereby ultimately tracking the most significant emission sink. Therefore,

Table 14
Partially nonparametric regression results: Effect of *EM* on *AGRIC*.

Variable	Coefficient
$AGRIC_{t-1}$	−0.1455*** (0.0282)
$AGRIC_{t-2}$	−0.1451*** (0.0288)
$AGRIC_{t-3}$	−0.1370*** (0.0289)
GDP_t	−0.0164 (0.0229)
PO_t	0.0463 (0.0522)
GDP_{t-1}	−0.0269 (0.0241)
GDP_{t-2}	0.0370 (0.0241)
GDP_{t-3}	−0.0484** (0.0203)
PO_{t-1}	0.1531** (0.0631)
PO_{t-2}	−0.0439 (0.0670)
PO_{t-3}	−0.1297** (0.0631)
EM_{t-1}	−0.0291** (0.0124)
EM_{t-2}	0.0004 (0.0131)
EM_{t-3}	0.0254** (0.0127)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 15
Non-parametric estimation of the effects of *EM* on *AGRIC*.

	Observed estimate
Mean	3.7125*** (0.0098)
Effect	−0.0047 (0.0057)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

of particular interest is the influence of forest (*FOR*), agriculture (*AGRIC*), and land use (*COMP*) on total greenhouse emissions (*EM*) and vice versa.

5.1. The nexus between forest and GHG emissions

Herein, we appraised the bidirectional relationship between forest and GHG emissions. However, it was discussed from the context of GDP and *PO*, which has not been addressed in preceding studies. From our evaluation, *FOR* has a positive influence on *EM*, where a 10 % increase in deforestation activities would accelerate the occurrence of *EM* by 3.9 %. In a previous study, a 1 % positive shock in forest area (deforestation) increases CO_2 emissions by 42 %, whereas a 1 % negative shock (afforestation) decreases CO_2 by 2.80 % (Abbasi et al., 2021). Similarly, investigations by Raihan (2023) and Raihan et al. (2023b) inferred that a 1 % increase in forest area would plummet GHG emissions by 3.46 % and 3.94 %, respectively. Forests serve as important global carbon sinks; hence, it is not unreasonable to predict their direct relationship with GHG emissions. For example, an eighteen-year satellite observatory on forest-related disturbances revealed a global gross GHG emission of 8.1 ± 2.5 $GtCO_2e$/yr, where CO_2 and CH_4 were emphatically dominant (Harris et al., 2021). The distribution of observations suggested a sufficiently strong relationship between *EM* and *FOR* (Fig. 1b), where the average positive effect of *FOR* earlier mentioned was evinced through a plot showing, largely, moderate increases in *EM* per advancement in forest area being encroached. Under this condition, the positive and significant effects of *PO* were observed as contributory to increasing *EM* quotients, albeit with low elasticity, thereby implying that its effect might not be significant enough to prevent a steep reduction in *EM* when *FOR* is reduced drastically. Therefore, we ratiocinate that deforestation and its subsequent contribution to GHG emissions might not be attributed to anthropogenic activities alone, but also to other natural causes of abiotic or biological origin, such as wildfires, blizzards and storms, the infestation of insects and parasitic microorganisms, which is corroborated by Robinne (2020) and references therein. For instance, during an investigation on the possible drivers of forest biomass losses, Fei et al. (2019) observed that 15 most damaged non-native invasive species – comprising 9 pathogens, 4 sap-feeders, 1 wood/phloem-borer, and 1 foliage-feeder – caused live feedstock mortality rate of 5.53 TgC per year. This metric was surmised to be similar in magnitude to fire-induced biomass losses and was further estimated to pose a severe risk to 41 % of total live forest biomass. Although deforestation has been surmised in our study as the major contributor to GHG emissions, we further explain that *FOR* might be a blanket variable to represent deforestation and forest degradation that result from natural or anthropogenic causes. This categorization gives a robust prediction because earlier studies have identified the omission of forest degradation, despite it being critical to GHG emissions and socio-economic development inventories (Pearson et al., 2017). Forest degradation simply refers to the direct human-effected reduction of forest carbon stocks through the invasion of canopy cover at rates insufficient to be considered as deforestation. Major causes of this phenomenon include the biased felling of certain tree parts or species for timber, charcoal, or for building make-shift camps in crisis-ridden locations or areas with poor amenities and low standards of living. This is common in East Africa, for instance, amidst modest improvement efforts in rural electrification in Uganda, charcoal and firewood consumption secures not less than 90 % share in the local energy utilization apportionment. The consequent upsurge in deforestation has birthed the espousal of green charcoal, in order to combat indiscriminate extraction of charcoal feedstock from forests. We observed the weak mixed but mainly negative effects of GDP and *AGRIC*, which implies the slight influence economic development and agriculture might have in reducing deforestation-implicated GHG emissions. This corroborates our thoughts that current smart energy technology investments and improved precision technology in agriculture and improved cropland management will only plateau GHG emissions until the advent of another era of disruptive innovation that would permit further visible decline. Although Mikayilov et al. (2017) had easier evinced that economic growth installs tremendous carbon emissions, with no latency and turning point in accordance with EKC hypothesis. The analysis by Zhou et al. (2018), which was rationalized from the assessment of developing (Brazil, China, India, Mexico, and South Africa) and developed (EU, USA, Canada, and Japan) countries, supports the EKC hypothesis that environmental degradation rises at the initial stages with increasing economic growth and finally decreases when high-income levels have been attained. In a similar vein, whilst some authors propose contrasting phenomena regarding the potential contribution of cropland-invested land use to the intensity of GHG emissions, other studies stressed that optimal land management practices are a critical approach to mitigating current GHG emissions (Sha et al., 2022). Here, they further noted that grasslands and croplands have swifter and more sensitive feedback from anthropogenic activities. Conversely, when assessing the effect of *EM* on *FOR*, we observed that it was rather not significant, with an inconsequential negative coefficient, due to the almost equal distribution of positive and negative elasticities amongst the observations (Fig. 4b). This was corroborated by a flat curvature (Fig. 4a), indicating no substantive effect of *EM*. However, in this scenario, the net influence of GDP is statistically significant, with a positive elasticity. This implies that aggressive economic development might contribute to accelerated and experiential deforestation due to the socio-economic predilections that accompany an improved standard of living. This observation is corroborated by Sarkodie and Owusu (2022); however, they maintained that the magnitude of deforestation due to accelerating economic growth. Moreover, Ajanaku and Collins (2021) and

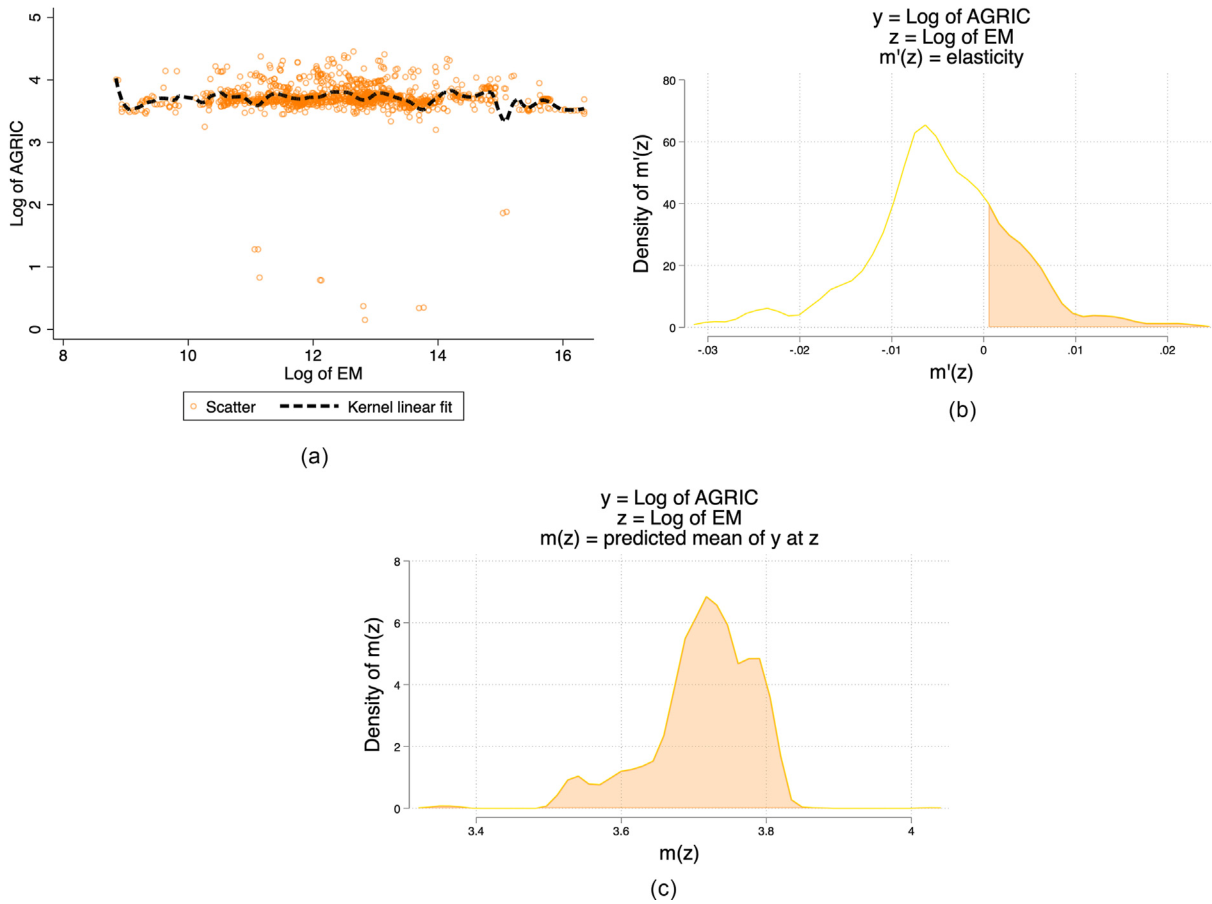

Fig. 5. The effect of GHG emissions on agriculture. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 16
Lasso regression results: effect of *EM* on *COMP*.

ID	Description	lambda	No. of non-zero coeff.	Out of sample R-squared	CV mean prediction error
1	first lambda	0.1212	1	0.0162	0.1247
42	lambda before	0.0027	51	0.6161	0.0487
43 *	selected lambda	0.0024	55	0.6162	0.0487
44	lambda after	0.0022	56	0.6162	0.0487
48	last lambda	0.0015	69	0.6149	0.0488

Notes: * lambda selected by cross-validation.

Table 17
Partially nonparametric regression results: Effect of *EM* on *COMP*.

Variable	Coefficient
$COMP_{t-3}$	−0.0389 (0.0263)
PO_t	0.0379*** (0.0146)
GDP_{t-1}	0.0196** (0.0086)
GDP_{t-2}	−0.0370*** (0.0093)
PO_{t-1}	0.0479** (0.0132)
EM_{t-1}	−0.0173** (0.0078)
EM_{t-3}	0.0214*** (0.0073)

Notes: country and time coefficients are not reported for brevity. Standard Errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 18
Non-parametric estimation of the effects of *EM* on *COMP*.

	Observed estimate
Mean	3.1000*** (0.0065)
Effect	0.0096*** (0.0035)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap Standard Errors are reported in parentheses. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

Caravaggio (2020) provided a fresh perspective on the matter, since they identified the trade of forest products as a causal effect of net deforestation. Trees have different carbon capture rates at different life stages; in their early and active growth rates carbon sequestration is more than emission; nonetheless, a balance is maintained between sequestration and emission at maturity, till the collapse stage where emissions supersede the capture rates (Von Essen et al., 2019; Roibas et al., 2018). This might explain the mildly negative effect of *EM* observed in our findings.

5.2. The nexus between agriculture and GHG emissions

In a world overstretched by population explosion, it is not unreasonable to assume agriculture underpins the sustenance of current human welfare. In the same vein, it is critical to understand

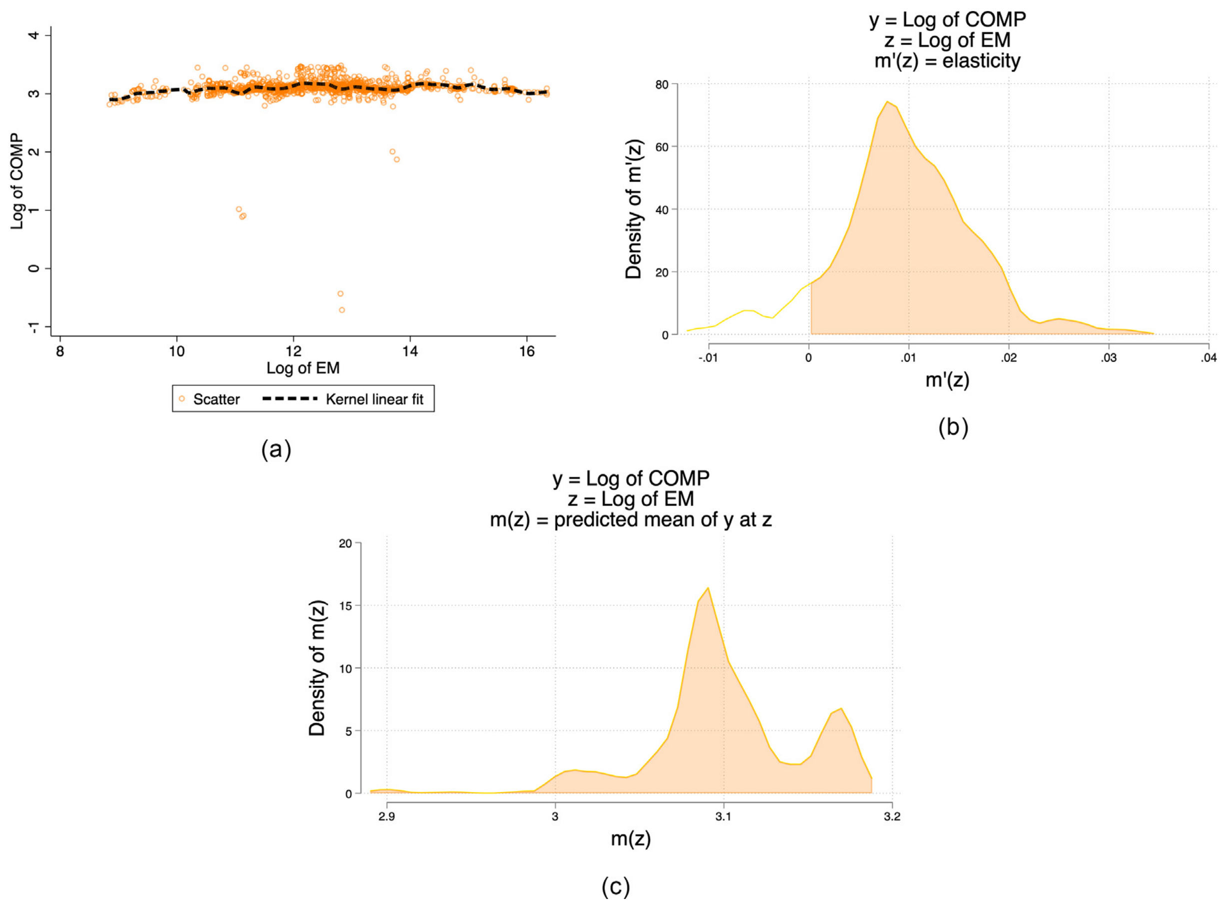

Fig. 6. The effect of GHG emissions on a composite variable. (a) The pattern of the kernel local linear estimation of *m(z)*. (b) Distribution of the predicted partial effect *m'(z)*. (c) Distribution of the predicted average *m(z)*.

Table 19
Panel pairwise causality tests.

Null Hypothesis	*F*-Statistics
GDP$\nRightarrow$EM	1.4901 (0.2257)
EM$\nRightarrow$GDP	8.9272*** (0.0001)
PO$\nRightarrow$EM	10.0876*** (0.0000)
EM$\nRightarrow$PO	0.4191 (0.6577)
AGRIC$\nRightarrow$EM	0.0350 (0.9656)
EM$\nRightarrow$AGRIC	0.5811 (0.5594)
FOR$\nRightarrow$EM	0.1608 (0.8515)
EM$\nRightarrow$FOR	0.5208 (0.5942)
COMP$\nRightarrow$EM	4.0141*** (0.0000)
EM$\nRightarrow$COMP	2.5579 (0.3393)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. P-Values in parentheses.

the role it might play in GHG emissions. Cropland expansion in the US has been reported to cause an upsurge in carbon emissions (Spawn et al., 2019). However, after observing the disproportionate contributions of certain cropping practices and croplands to emissions, Carlson et al. (2016) posited an antithetical view that GHG emissions are largely dissociated from production intensity across crops and countries. From our evaluations, *AGRIC* has a sparingly significant effect with a negative elasticity (-0.09). This implies that a 10 % increase in agricultural activity or cropland expansion would only reduce *EM* by nearly 1 %, which is indeed minimal, given the magnitude of agricultural activities undertaken at present globally, and the diminishing returns they likely have on deforestation. Raihan (2023) and Raihan et al. (2023a) reported a 0.20 % and 0.22 % decline in GHG emission per 1 % increase in agricultural productivity, where they reiterated its importance in harvesting atmospheric CO_2 for conversion into biomass or soil carbon. After taking inventory of the effects of livestock and crop production on CO_2 emissions using both linear and non-linear models, Zhou et al. (2022) discovered that livestock farming could reduce CO_2 in the short- and long-run. They further observed that increased crop production could deteriorate environmental quality in the short-run, whereas in the long-run the effect might be insignificant or mixed, depending on the shock in productivity. Therefore, it is not illogical to reason that forest encroachment of cropland expansion is not a prudent initiative toward the perpetual reduction of global emissions. This outcome is further illustrated by a negative, yet not-so-strong relationship between *EM* and *AGRIC*, as a result of a negative elasticity of less than 1, where the majority of observations were between -0.10 and 0.05 (Fig. 2b). Also, Fig. 2a shows a non-linear curvature, especially from log 2 onwards for *AGRIC*, where a shoulder occurred at log 2.5 and decreased to 3.5 before a gentle and steady increase in *EM*. Although this outcome might not be absolutely certain due to heterogeneity in the observation's cloud, we can surmise that this phenomenon (low decreasing returns of *EM* to *AGRIC*) might attain some constancy unless interrupted by other external factors. For instance, population growth and urbanization have been reported by several authors to contribute to emissions of GHGs traceable to agriculture, such as CO_2, N_2O, and CH_4 (Aziz and Chowdhury, 2023; Raihan, 2023; Raihan et al. 2023a; Rehman et al., 2022a). In fact, the interaction of food production, urban, and rural population growth exposed an adverse impact on CO_2 emissions (Rehman et al., 2022a) In this regard, we observed the influence of *PO* as emphatic, with a high elasticity of 1.27, which is sufficient to influence *AGRIC* contribution to *EM* through other channels such as agro-industrial activities, food wastes, and losses. For instance, after the increased expansion of croplands by 12 % in the last 50 years not less than half of global croplands have been earmarked for food production (Roka, 2019). However, about 30 % of these croplands produce foods that navigate the supply chain without consumption and constitute major GHG remittances, especially cereals (31 %) and vegetables (21 %) (Unuofin et al., 2021). Besides, GDP has a mixed but net negative influence; this is because economic development is assumed to not only adversely impact the *AGRIC-EM* nexus at the developmental stages but will also have little to no effect or minimally reduce the likelihood of *AGRIC*-implicated GHG emissions, due to our advancement towards a circular economy. For instance, biochar embodies the fruition of a circular bioeconomy and has been identified as one of the technologies devised to convincingly curb GHG emissions in the immediate future. This is because it epitomizes the upcycling of agro-industrial and forest residues and other solid wastes in a process that also involves the production of bio-oils that can be amended into liquid transport fuel, hence, affecting carbon–neutral energy production. Moreover, biochar can serve as carbon sinks, nutrient vaults, and scrubbers in the soil, thereby preventing land degradation (due to its longevity), permitting land reuse, and forestalling cropland extension. Our submission is corroborated by a US-based study, where the willingness to purchase and apply biochar was based on economic capacity relative to crop prices, however, the authors observed a reduction in total crop area due to biochar-enabled high returns (Dumortier et al., 2020). However, Rehman and Rehman (2022) and Chen et al. (2022) stated that population growth, urbanization, and economic growth might boost environmental degradation and GHG emissions. In particular, Chen et al. (2022) inferred a bidirectional causality between economic growth and carbon emissions, economic growth and urbanization, economic growth and population growth, as well as the causation from urbanization to carbon emissions. Reversely, we observed that the non-parametric effect of *EM* on *AGRIC* is not significant. This was further ascertained by a flat curvature (Fig. 5a), a reduced number of observations with small positive elasticities (Fig. 5b), as well as a symmetric and homogenous pattern of predictions (Fig. 5c), thus, emphasizing that *EM* has no appreciable effect on *AGRIC*. We believe that this quiescent effect might be attributable to the relativity of crop requirements, atmospheric warming and its associated biotic and abiotic factors will differ amongst vegetable and cereal plantations. For example, in a recent study, while maize crops experienced a dip in productivity due to atmospheric warming, wheat yield was particularly enhanced (Jägermeyr et al., 2021). From the purview of European agricultural systems, Carozzi et al. (2022) foreshadow a stable production in the first half of the century, and a further decline during the second half, especially in low-latitude regions due to the reduced length of the growing cycle. The analysis by Rehman et al. (2022b) showed a mixed effect of GHG emissions on some agricultural and climate-related parameters. They observed that while wheat, maize, sugarcane, cotton, bajra, gram sesamum crops, and land use exhibit a positive correlation with CO_2 emissions, temperature, rainfall, rice, jowar, and barley evinced a negative relationship with CO_2 emissions. Notwithstanding, we did observe a strong autoregressive interaction of *AGRIC*, however with negative elasticities. On this note, we propose that intensive farming on cropland would lead to degradation and agricultural activity, input or productivity will further decline in successive periods of time under a regime impacted by GHG emissions. Cropland expansions and intensification of agriculture are major influencers of land degradation that most times lead to desertification, thus, the soil is rendered helpless against elements of climate change. Regrettably, the extent of current agricultural land degradation portends an impediment to implementing sustainable agricultural practices, despite the unanimous and keen interest of farmers in restoring and maintaining soil health worldwide.

5.3. The nexus between land use and GHG emissions

Previously, we addressed the individual effects of *FOR* and *AGRIC*, however, they comprise elements whose effects might have been overlooked due to generalization. Therefore, we considered a fine-tuned observation where we evaluated the composite measures of land use variables, such as arable land, permanent pastures, cropland, and forest. Interestingly, we observed that *COMP* has a highly significant effect on *EM*, with a high positive elasticity of 0.70, which suggests a 7.1 % increase in *EM* per every 10 % increase in *COMP*. Although this outcome has a low *R*-squared value (12 %), its reliability was confirmed through certain instances. First, its curvature is not linear as it portrays a shoulder in *EM* at log 2 of *COMP*, then a steady increase at log 2.5. Moreover, its observation cloud is rather concentrated, which is characteristic of desirable reliability (Fig. 3a). Second, all observations show a positive elasticity close to 1, where a large mass of observations are concentered between 0.6 and 0.8 (Fig. 3b), thereby suggesting a strong and positive relationship between the two variables evaluated. Third, the weak variance around the mean of distribution peaks substantiates that predictions of *EM* to different levels of *COMP* are satisfactorily homogenous. We believe this outcome emphasizes the concatenation of composite land use variables and their interrelation in strengthening the GHG emissions budget. Composite measures of land use variables emissions and removals comprised approximately 21 % of global GHG emissions in 2018 (Lamb et al., 2021), where data fingerprinting identified major pathways of emissions as (i) deforestation (mostly cropland extension), (ii) imbalanced wood harvesting, (iii) peat drainage and burning, (iv) reforestation and periodic restoration of other natural vegetation, (v) interconversion between croplands and pasture, (vi) soil CO_2 flux due to grassland and cropland management, (vii) overgrazing and enteric fermentation from pasture animals (livestock), (viii) manure management, and (ix) synthetic fertilizer application. However, these global trends tend to exhibit disproportionate patterns, regionally. Typically, not less than 50 % of CO_2 emissions in developing regions (Africa, Latin America, and Southeast Asia) are attributed to composite and used variables, especially agricultural expansion through biomass stockpiling and incineration and carbon leaching from laden soils (Hong et al., 2021; Pearson et al., 2017). Although developed nations (EU, USA, Canada, and Japan) only practiced high land clearing rates until the 20th century, such that their land use emissions are now negligible (Pongratz and Caldeira, 2012), recent reforestation and rejuvenation of abandoned land in Europe have accorded them a larger remittance of N_2O and CH_4 emissions from composite land use compared to tropical, developing countries (Hong et al., 2021). It was also observed that *PO* has a strong and positive effect on *COMP*-implicated GHG emissions, with an elasticity of 89.9 %, which is phenomenally high. This implies that an increased urban population would warrant an upsurge in the activities classified within the land-use variables and hence a further increase in GHG emissions. Similarly, Lamb et al. (2021) noted that emissions from 2010 to 2017 have been affected by increases in population, especially in actively growing regions, such as Africa, the Middle East, Southern Asia, Southeast Asia, and the Developing Pacific. Moreover, CO_2 emissions from land use elements were shown to be consistent with a significant expansion of anthropogenic land demand and use between 1990 and 2018 (Hurtt et al., 2020). Indeed, the land is the sine qua non yet limiting resource for enabling the production of food, feed, timber, and bioenergy inter alia, instigated by the growing human population, diverse dietary patterns, and production efficiency (Kastner et al., 2012). To substantiate this, humans have expanded cropland areas (9.1 %), secondary forests (22.5 %), and urban land (64.3 %), thereby simultaneously subduing primary forest area by −12.9 %, which have been spearheaded by Africa, Latin America, and Southeast Asia (Hurtt et al., 2020). This trend might attain constancy, until proper land management, proper consumer behavior, and urban and regional planning are fostered, and emission deficit technologies and regimes are enabled. On the other hand, we observed that although *EM* has a statistically significant effect on *COMP*, it was rather very small with a positive elasticity of 0.01 %. This claim was substantiated by the flat curvature in Fig. 6a and the mass of observation between 0 and 0.02 portrayed in Fig. 6b. Even so, we surmise that *EM* might have a stronger, non-negligible impact on land use variables in the long run. It is evident that emissions-impacted climate change will have a mixed effect globally due to regional and latitudinal differences. While atmospheric warming would lengthen the growing season in the middle and higher latitudes of the northern hemisphere and may permit crop productivity (Deryng et al., 2016; Yang et al., 2015). Crop yields are negatively impacted by soaring seasonal rainfall variability, drought severity, and growing season temperatures in the tropics, sub-tropics, water-limited, and high-elevation environments, as well as drought severity and growing season temperatures (Müller et al., 2017; Wheeler and Von Braun, 2013). When these effects are viewed collectively, it is not inaccurate to assume that the current net effects of GHG emissions on the land use variables are slightly mild. Ultimately, this would in the long-run cause frequent and disorganized migratory patterns of indigenous fauna, further driving skewed biodiversity and distortion of the food web.

Altogether, we detected the unidirectional flow from GHG emissions to forestry, agriculture, and land use through parametric tests, thereby supporting the premise that environmental pollution's effect on land use variables is not too negligible to be overlooked. From a non-parametric approach, the significant effect that forests and agriculture have on GHG emissions was observed, whereas a bi-directional link was established between GHG emissions and land use. When our novel approach was compared with traditional causality analyses (Table 19), they confirmed the non-existent influence of forestry on GHG emissions. However, we also observed the absence of a statistical causal flow for the forestry emissions and agriculture-emissions nexuses. Interestingly, we detected a unidirectional causal link from land use (F = 4.01) and urban population (F = 10.09) to GHG emissions, respectively, thus emphasizing the direct link between these two and GHG emissions.

6. Conclusions and policy recommendations

Global warming might continue to be a pressing issue, even after the set ultimatum for achieving carbon neutrality and the 1.5 °C warming limit. This is partly because scientists and policy-makers at large have not been able to accurately capture the dynamics of GHG emissions with regard to their pathways, despite being knowledgeable of the prominent GHGs. In this regard, we identified gaps in the literature regarding the analysis of the interactions of forest density, cropland, and land use (composite variable) with GHG emissions. Thus, this study employed a robust statistical approach in evaluating the present relationships between forest, cropland, land use, and GHG emissions, with regard to economic growth and urban population. Here, we were able to evidently demonstrate that population does influence all land use variables and their consequent contribution to the GHG emissions budget. We also observed that economic development could mitigate GHG emissions through technology and innovation, however, it might be subject to consumer behaviour and productivity––as we observed both positive elasticities for GDP with regard to its influence on forests––which might augur further contributions of forests to emissions. Forest density has a strong effect on global anthropogenic GHG emissions because it is regarded as a carbon sink and a major determinant in atmospheric warming or cooling. Therefore, efforts could be made to reduce forest thinning, through the search for sustainable alternatives to their products usually adopted as feedstock for energy or as structural materials. Governments worldwide should strengthen their policies regarding land use, forest management, urbanization, and agriculture in order to further mitigate GHG emissions. They could revise their international trade policies into more transparent modules in order to effectively track the shortfalls in policy adherence. Certain policies could include the preservation of woody biomass that has an immense capacity for carbon storage, while the old live biomass with low storage capacity could be used for timber. Moreover, the rate of reforestation should supersede the rate of such deforestation. Due to the rapid rate of urbanization and industrialization of once-natural environments, concerned stakeholders and investors could be mandated, also incentivized by governments to include environmental sustainability in their respective blueprints for real estate and industrial layouts. Sustainable agricultural practices that will prevent the loss of fertile soil and will ensure the restocking of soil carbon sinks from atmospheric CO_2 must be pursued. The results of this study, although robust, further exposed the existence of uncertainties and unknowns, whose seemingly trifling quotients might be strong determinants for long-term environmental degradation and GHG emissions. In this regard, certain themes such as demography, seasonality, population diet preferences, crop type, and mode of farming, inter alia, should be analyzed in future studies, especially in the context of the themes here discussed.

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CRediT authorship contribution statement

Cosimo Magazzino: Conceptualization, Validation, Data curation, Supervision, Writing – review & editing, Visualization. **Giovanni Cerulli:** Methodology, Investigation, Software. **Ilham Haouas:** Writing – original draft. **John Onolame Unuofin:** Writing – original draft. **Samuel Asumadu Sarkodie:** Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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