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The nexus between agricultural land use, urbanization, and greenhouse gas emissions: Novel implications from different stages of income levels

Cosimo Magazzino[a,*], Giovanni Cerulli[b], Umer Shahzad[c], Salahuddin Khan[d]

[a] Department of Political Science, Roma Tre University, Italy
[b] National Research Council of Italy, Italy
[c] School of Economics, Széchenyi Istvàn University, Hungary
[d] College of Engineering, King Saud University, Saudi Arabia

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ABSTRACT

The current study establishes theoretical and empirical linkages among urbanization, economic growth, land use, and greenhouse gas (GHG) emissions. The prime objective of this article is to draw novel conclusions and policies for the different income levels of countries regarding the urbanization and agriculture sector land on environmental pollution. Employing panel data of 50 countries for the period 1990 to 2019, this study uses the lasso regression and non-parametric regression panel data methods to investigate the impacts of land use (arable, permanent pastures, and cropland), urbanization growth, and economic progress on the pollution levels. After estimating a Lasso regression to find the best auto-regressive predictive specification, we used an auto-regressive partially linear regression where each of the drivers' effects was modelled non-parametrically. The elasticity effect of the urban population on emissions is significantly positive and sizable. In addition, the effect distribution shows a non-negligible share of observations with an elasticity higher than one. Urban population growth is a serious threat to climate change, as it seems to increase sharply CO_2 emissions (although with an elasticity pace smaller than one). The elasticity effect of GDP is significantly negative, which implies that the scale of production, by triggering efficiency, can have a positive effect on emissions reduction. The results argue that agglomeration negative effects put in place by larger urban population can partly explain this finding. Overall, the study argues that urbanization growth and economic activities lead to GHG emissions, whereas the study also discusses novel implications and the role of agricultural land use apropos Sustainable Development Goals (SDGs). The empirical findings allow us to draw novel conclusions and guidelines in line with SDGs. The agricultural reforms might include irrigation and farming techniques such as spin farming, solar tube wells, tunnel farming, technology use agreements, plant double helix, etc.

1. Introduction

Climate change is a serious threat and challenge for the human race. The increasing temperature, environmental repercussions, land deterioration, rainfall fluctuation, precipitations, ecological deficit, and greenhouse gas (GHG) emissions are serious challenges to the survival of economic and non-economic sectors. Environmental issues and rising pollution have become a serious threat to agriculture, industrialization, and food security. More specifically, the fluctuations in temperature, heatwaves, precipitation patterns, floods, and extreme weather jeopardize agriculture productivity. Among all these, GHG emissions are important drivers of human-induced environmental issues. The agriculture sector contributes more than 10 to 15 percent of global GHG emissions, which includes emissions from enteric fermentation (methane, CH_4), synthetic fertilizers (nitrous oxide, N_2O), and tillage (carbon dioxide, CO_2) (Tubiello et al., 2013; Jantke et al., 2020). According to emission pathways, there is a need to mitigate 48% of global agricultural CH_4 emissions until 2030 relative to 2010 levels and nitrous emissions by 26%, to attain the global warming of 1.5 °C. In addition, Agriculture is one of the key sector sectors affected by climate change and global warming, and it also contributes to environmental externalities (UNFCCC, 2021). According to the Food and Agriculture

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* Corresponding author.
E-mail addresses: cosiimo.magazzino@uniroma3.it (C. Magazzino), giovanni.cerulli@ircres.cnr.it (G. Cerulli), shehzad-umer@hotmail.com (U. Shahzad), drskhan@ksu.edu.sa (S. Khan).

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Organization (FAO) of the United Nations (UN), innovation and efficient technology in the agriculture sector are important to move toward limiting CO_2 emissions and saving biodiversity (FAO, 2021).

The fluxes of GHG emissions have increased over the past decades. For instance, only from 2005 to 2016 GHG emissions augmented from 38,679 to 46,141 mt of CO_2 equivalent (Si et al., 2021). A group of G-20 countries accounting for approximately 75% of global GHG emissions, two-thirds of the world's population, and 80% of global GDP, has a critical role in tackling climate change (World Resources Institute, 2021). According to the Intergovernmental Panel on Climate Change (IPCC, 2021), each of the past four decades has been successively warmer than all the decades before it since 1850. During the first two decades of the 21st century (2001–2020), the global surface temperature was 0.99 (0.84–1.10) °C higher than that of 1850–1900.

The Environmental Protection Agency (2018) suggests that the most significant kinds of GHG emissions comprise CO_2, N_2O, CH_4, and water vapors. Several factors contribute to the degradation of the environment quality following the spread of CO_2 emissions worldwide. The consumption of coal, natural gas, and petroleum energies leads to an increase in GHG emissions. Approximately 5% of all CO_2 emissions from human activities flow from one country to another. Around 50% of carbon emissions are associated with trade commodities (steel, cement, and chemicals), and the rest is associated with finished and semi-finished products (clothing, motor vehicles, industrial equipment, and machinery). For many developed countries, embodied carbon imports are significant. Developed countries are typically net importers of carbon emissions, while developing countries export embodied carbon emissions (Carbon Trust, 2011).

Carlson et al. (2017) argued that agriculture is the main source of carbon dioxide emissions and global warming. Furthermore, agriculture and land use contribute to around 25% of direct and indirect GHG effects (CO_2, CH_4, and N_2O) to global anthropogenic GHG.

Nevertheless, some environmental issues (acid rain and ozone depletion) are caused by the high volume of nitrogen used in fertilizer applications in farmland and wasted (Adegbeye et al., 2020). Recently, more interest in the emissions of GHG derived from vegetable products (Zhang et al., 2017). The energy sector contributes around 75% of GHG emissions (IEA, 2021). The carbon dioxide emissions from the global energy sector rise to almost 38 gigatons (around 1.9%) between 2013 and 2018. In 2020, the world energy demand registered the largest decrease since the Second World War, almost 4%, and around 5.8% in world energy-related CO_2 emissions (REN21, 2021).

Increasing fossil fuel demand is the major factor causing carbon dioxide emissions (Alola, 2019). In 2021, according to the 26th Conference of the Parties (COP26), the Intergovernmental Panel on Climate Change (IPCC), the temperature of the global surface had been warmed by 1.1 °C in comparison with the pre-industrial epoch. Reducing GHG emissions and achieving net-zero carbon dioxide emissions contribute to stabilizing the temperature of the global surface and limiting warming to 1.5 °C (IEA, 2021). According to the United Nations environment program (UNEP), the main goal of the Paris climate agreement is to limit temperature to less than 1.5 °C this century and in the next 8 coming years (2030). In the short term, to fill the emission hole and decrease the temperature, the reduction of GHG emissions (CH_4) in different sectors (agriculture, waste, and fossil fuels) could mitigate climate change (UNEP, 2021).

The policymakers and the administration management identify the greenhouse effects of agricultural output and elaborate policies to mitigate climate change. (He et al., 2021). Earlier research elaborates strategies and measures at region-specific scales, farmers, and crops to limit GHG emissions and mitigate climate change (Zarei et al., 2019). To keep global warming below 2 °C for the coming years 2050 and respect the limited level of GHG in fact of increasing demand for food and population (Shahzad et al., 2021). The world population is estimated to increase from around 8 billion to 8.5 billion in the coming years (2030) and 9.7 billion in 2050 (IEA, 2021). Food and Agriculture Systems Foresight Study (2020) indicated that the environment and agriculture had an opposite association on one side agriculture contributes to climate change and environmental damages and on the other side, agriculture is a victim and depends on environmental degradation (land, water, and genetic materials).

Renewable energy, innovations, and new technologies are the main solutions to resolve environmental issues and mitigate climate change by limiting anthropogenic global warming (Ghazouani et al., 2020). Investment in energy efficiency and renewable energy is crucial to limiting global warming and reducing carbon dioxide emissions. Both renewable energy and energy efficiency contribute to limiting GHG emissions. To realize the net-zero emission pledges, 190 countries noted renewable energy in their Nationally Determined Contributions (NDCs) under the agreement of Paris, whereas 144 countries noted energy efficiency and 142 nations mentioned both (REN21, 2021). The world bank group is working now on climate-smart agriculture. In the first climate change action plan (2016–2020) and the same for the coming update (2021–2025), nations committed with the world bank to realize reducing emissions, increasing productivity, and enhancing resilience by delivering climate-smart agriculture. The agriculture sector is financed by 52% of the World Bank's global financing and mitigating climate change and achieving climate change targets in 2020. According to the UN, 8.9% of the world population is hungry and this figure could increase to 840 million by 2030. The food demand increase with the increase of the world population and the need to produce more food becomes difficult. The world will need to feed 9 billion people by 2050 (almost 70% more food needed), and the food security challenge becomes hard. The negative effects of climate change and GHG influence agriculture's challenges to achieve its food needs.

The sustainable investment will keep productivity and maintain the future food demand. On the other hand, agriculture contributes to climate change (19–29% of global GHG), and the absence of measures will increase carbon dioxide emissions. The environmental situation becomes a challenge and climate change mitigation becomes a crucial help and need (World Resources Institute, 2021). The prime objective of the current study is to explore the impacts of agriculture and urbanization growth on greenhouse emissions. To this end, authors employ the data of different income levels of countries, which allows drawing a few novel implications apropos Sustainable Development Goals and agriculture sustainability. An important contribution of our study is that we used the composite measure of arable, permanent pastures, and cropland for the agriculture sector's contribution to GHG emissions. The conclusions of the current study reveal the non-parametric and lagged impacts of the agriculture sector and urbanization growth on GHG emissions. The findings of this study are in line with SDG-8: Decent Work and Economic Growth and SDG-12: Responsible Consumption and Production. Finally, the findings and conclusions will help policymakers design effective urbanization and agricultural land usage policies for sustainable and cleaner growth. Meanwhile, the empirical results can provide a reference for developed, emerging, and underdeveloped countries aiming to mitigate GHG emissions.

Given the highlighted research gaps, this paper contributes to the ongoing debate by pioneering the simultaneous assessment of the interaction among urbanization, economic growth, land use, 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. 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 2019, 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. Third, we evaluate the nexus using a novel estimation technique by employing Lasso regression and partially non-parametric 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 used 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 (Azomahou et al., 2006; Magazzino et al., 2021; Wang and Feng, 2021; Krüger and Tarach, 2022). However, this is the first to use a semi-parametric regression jointly with an ML optimal specification method.

The rest of the study paper is organized as follows: Section 2 reports the literature reviews together with research gaps. Section 3 provides data description and methodology. Section 4 presents and discusses the empirical results. Section 5 concludes the paper and puts forward policy implications based on the previous discussion.

2. Literature review and research gap

It is extensively important to measure the dynamic relationship between the advancement of agricultural activities and the propagation of GHG emissions. A few recent empirical studies have investigated the relationship between environmental indicators, urbanization growth, and agriculture using various techniques of estimation for different countries or panel samples (Wang and Su, 2019; Rehman et al., 2020; Sufyanullah et al., 2022). Studying the data for Pakistan, Sufyanullah et al. (2022) documented the impacts of urbanization and energy use on carbon emissions. The Auto-Regressive Distributed Lags (ARDL) bounds testing approach claimed a positive association between urbanization growth and carbon emissions. Rehman et al. (2020) discussed the relationship of CH_4 emissions, N_2O emissions, CO_2 emissions, and GHG emissions with the agricultural GDP for the case of China using the ARDL bounds testing approach, fully modified least-squares method, and canonical cointegrating regression analysis. The outcomes from the analysis revealed that both CO_2 emissions and GHG emissions have a positive influence on the agricultural gross domestic product. The findings argued that agricultural CH_4 emissions and agricultural N_2O emissions negatively influence the agricultural gross domestic product. They conclude that China is a huge emitter of CO_2 emissions and GHG emissions. The study recommends that the Chinese government should make the required changes to reduce emissions.

More recently, Niu et al. (2020) studied the global agriculture trade data and GHG emissions for 151 countries. The findings of quasi-input-output analysis suggested that international trade of agricultural products has different impacts on the pollution level of each country. For instance, the findings mentioned that Australia, the USA, Brazil, and Argentina are the largest exporter of agriculture products and greenhouse gas emissions.

In the same line, Wang and Su (2019) report that urbanization and industrial growth are positively linked with the carbon emissions of China. De Cara et al. (2005) used a supply-oriented, agricultural-type linear programming model of European agriculture, the reference levels of CH_4 and N_2O emissions are assessed at the regional level in the EU-15. The authors attempted to assess the potential reduction and the optimal combination of emissions sources for a range of CO_2 equivalent prices. Further, the authors show that spatial variability of the decrease attained at a given carbon price is significant, indicating that the heterogeneity of abatement costs is a fundamental characteristic in the design of a mitigation policy.

In the same line, Darwin (2004) examined whether climate projections generate uncertainty about the economic impacts of agriculture. Also, the author investigates to what extent the agricultural economic impacts of GHG emissions depend on the economic conditions at the time of the impacts. The results mentioned that the uncertainty due to varying climate projections is quite large for most of the economic effects assessed in the analysis. Also, the outcomes mentioned that, at the moment of the impact, the economic conditions have an influence on the direction and the magnitude as well as confidence in the economic effects of identical projections of GHG impacts. Global agricultural production is considered the most consistent economic variable. Increases in average global temperature lead to a decline in global agricultural production on average, under the economic conditions of 1990 and improved, and in both cases, confidence in varying climate projections is medium or higher. The author concludes that agricultural production can be a fairly robust indicator of the potential impacts of GHG emissions.

In one of earlier works, Muyungi and Omujuni (1995) attempt to identify and quantify the anthropogenic sources and sinks of GHG emissions from forestry, land-use change, and agriculture in Tanzania. The authors revealed that, according to the 1990 inventory, CH_4 and CO_2 are the main gases emitted in the land-use sector. Also, they deliberate that the main source of CH_4 was the enteric fermentation in animal production systems. Although deforestation results in GHG emissions, Tanzania's managed forests are an important sink of CO_2. Si et al. (2021) examine the short and long-run causal effects of agriculture, forestry, and land use on GHG emissions for the case of China using the Vector Error Correction Model (VECM). The outcomes of the empirical study suggest the existence of long-run cointegration among the variables. However, in the short-run, only land use significantly has a strong causality with GHG emissions in China. The findings recommend that Chinese policymakers should improve the activities related to agriculture and land use.

Some other empirical studies have considered that energy consumption (including renewable energies) influences agricultural activities through some land use forms. More recently, Koondhar et al. (2021a) investigated the relationships between bioenergy consumption, agricultural bio-economic growth, and CO_2 emissions for the case of China using ARDL bounds and novel Dynamic Auto-Regressive Distributed Lags (DYNARDL) models. The outcomes from the empirical modeling show that all variables are cointegrated using the ARDL bounds test. Also, an increase in the consumption of bioenergy leads to an increase in agricultural bio-economic growth in the short- and long-run. According to the DYNARDL model, the outcomes show that a 10% positive shock from the consumption of bioenergy will increase the growth of agricultural bio-economic, while a 10% negative shock in bioenergy consumption will decrease the growth of agriculture. Moreover, the study suggests that a negative shock from fossil fuels is able to increase agricultural bio-economic growth. However, a positive shock from fossil fuels will decrease the growth of agriculture. The authors recommend that to achieve carbon neutrality, it would be better to substitute fossil fuel with sources of bioenergy or renewable energy consumption. Similarly, Koondhar et al. (2021b) investigate the asymmetric causality between agricultural carbon emissions, energy consumption, fertilizer consumption, and cereal food production in the case of Pakistan using the Non-linear ARDL (NARDL) and linear and non-linear Granger causality tests. The outcomes from linear Granger causality suggest unidirectional causality running from energy consumption and fertilizer to cereal food production. However, the non-linear Granger causality suggests a unidirectional causality from cereal food production to agricultural carbon emissions and energy consumption. Also, the authors revealed unidirectional causality fertilizer consumption to cereal food production. The results from the NARDL approach show that changes in agricultural carbon emission, energy consumption, and fertilizer lead to fluctuations in cereal food production. The authors recommend that Pakistan farms should switch from chemical fertilizer, non-renewable energies to organic fertilizer, and renewable energy sources to mitigate emissions levels and increase the production of cereal food. Magazzino (2023) examined the relationship among ecological footprint, electricity consumption, and GDP in China using annual data ranging from 1960 to 2019. However, factors like trade openness, urbanization, and life expectancy might increase EF as ecological distortions are mainly human-induced. Quantile Regressions (QR) estimates indicate that electricity consumption and real GDP increase environmental degradation, while trade and urbanization reduce ecological footprint, allowing for a higher environmental quality. On the other hand, the spectral Granger-causality tests reveal that only urbanization and life expectancy affect environmental degradation over the whole frequency domain.

Ozturk (2017) discussed the dynamic relationship between agricultural sustainability and food-energy-water poverty for a panel of Sub-Saharan African (SSA) countries using pooled least squares regression, pooled fixed effects, and pooled random-effects regression techniques. The results of the empirical study show that the country-specific shocks influenced the model of food-energy-water poverty. Also, the author shows that agricultural value-added, cereal yields and forest area decrease the food-energy-water poverty relationship. This outcome leads to higher economic growth and price levels at the environmental quality cost. Few recent studies have considered the role that renewable energies and agricultural activities play in mitigating pollution levels. Turkey is one of the most important countries in agriculture production, despite the share of service and industry observed in constant rise. Adedoyin et al. (2020) explored the relationship among agro-economic performance, real GDP, total natural rent, urbanization, and environmental degradation in a carbon function using a panel dataset for the period 1980–2014 for selected SSA countries. Empirical findings assert that agricultural value-added reduces emissions while urbanization and natural resource rent both increases CO_2 emissions in the long-run. Bayrakcı and Koçar (2012) investigated the use of renewable energies (such as solar energy, biomass energy, wind energy, geothermal energy, and hydropower) in agricultural activities in Turkey. The authors recommend some proposals like substituting renewable energy instead of fossil fuels. Kara et al. (2022) examined the carbon emission effects of the categories of agricultural land utilization for Turkey over the period 1988–2019. By employing the ARDL approach, the study finds that the use of agricultural land for arable farming and permanent plantation helps to reduce carbon emissions, especially in the long-run, while the impact of meadows is also desirable only in the short-run. Bas et al. (2021) inspected the environmental effects of the contributions of agriculture value-added, merchandize value-added, export value-added, and share value-added in Turkey over the period 1991–2019. By employing a combination of econometric techniques, the result revealed that agriculture value-added and export value-added mitigate environmental hazards, while a 1% increase in total energy utilization, merchandize value-added, and share value-added induce carbon emission by about 0.6%, 0.02%, and 0.001%. Ben Jebli and Ben Youssef (2017) examined the role of renewable energy consumption and agriculture in mitigating CO_2 emissions for a panel of North African countries using panel cointegration techniques and Granger causality tests spanning the period 1980–2011. Interestingly, the outcomes revealed a bidirectional short-run causality between CO_2 emissions and Agriculture Value-Added (AVA), one-way causality from agriculture to economic growth and from renewable energy consumption to AVA. Moreover, the authors show a bidirectional long-run causality between emissions of CO_2 and agriculture and unidirectional causality from renewable energy consumption to emissions. From Fully Modified Ordinary Least Squares (FMOLS) and DOLS (Dynamic Ordinary Least Squares) approaches, long-run estimates show AVA mitigates emissions in the long run. For the case of Brazil, Ben Jebli and Ben Youssef (2019) have investigated the dynamic association between Combustible Renewables and Waste (CRW) consumption, agriculture, CO_2 emissions, and economic growth using the ARDL bounds approach and Granger causality test. The results mentioned that all variables are integrated of order one and the long-run association between the variables has between established. Bidirectional long-run causalities between all the variables are proven. Long-run estimates show that both consumptions of CRW and agriculture contribute to mitigating CO_2 emissions. Magazzino and Santeramo (2023) analyzed the link among financial development, productivity and growth on a sample of 130 economies over the period 1991–2019. The results show that higher levels of output stimulate the economic development in the agricultural sector, mainly via the productivity channel and, in the most developed economies, also through access to credit. Differently, in developing and least developed economies, the role of access to credit is marginal.

From the above discussion and comprehensive analysis of literature, the authors observe a strong window of research gap regarding the impacts of the agriculture sector on greenhouse gas emissions. Hence, the investigation into the role of agriculture for environmental externalities is a logical and sound mind. More specifically, the current study uncovers the impacts of three composite agriculture measures: arable, permanent pastures, and cropland for agriculture. This aspect of empirical investigation has been overlooked in the existing literature. Hence, the findings on-hand study are more in-depth and report novel conclusions and fruitful policies. Further, the findings of this study allow us to draw some novel implications regarding SDG-8: Decent Work and Economic Growth and SDG-12: Responsible Consumption and Production.

3. Data and methodology

3.1. Data

The global sample includes 50 countries across all development levels throughout 1990–2019. 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) database from World Bank (WB), freely available on the internet. The total GHG emissions 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, GHG emissions, which comprises CO2, CH4, N2O, and fluorinated gases. EM is the total GHG emissions (in kt of CO2 equivalent); GDP is the real Gross Domestic Product (in constant LCU); PO is the urban population (% as country's total population); DEN is the composite measures of arable, permanent pastures, and cropland. 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. All the variables in the model are presented in terms of the natural logarithm.

All variables are constructed in natural logarithm to reduce data's variation. Descriptive statistics of the variables are given in Table A in the Appendix. Figure A contains the scatterplot matrices of the selected series.

3.2. Methodology

In this study, we jointly use optimal model specification through the Lasso method, and a partially non-parametric 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 (Cerulli, 2015). 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 non-parametric autoregressive equation in a panel data context. The underlying regression for N cross-sectional units observed over T periods is modelled as follow:

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

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 $\varepsilon_{i,t}$ a pure error shock with zero mean and finite variance. The main goal of our analysis is to estimate $m(\bullet)$ conditional on the country and time fixed effects and the auto-regressive components of the dependent and independent variables. We also assume that $K = 3$, to account for at most a three-year autoregressive process.

In equation (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. Thus, we run a Lasso regression of equation (1) by dropping out $m(z_{i,t})$. The Lasso is a machine learning 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 prediction bias and prediction variance. There is predictive superiority of Lasso compared to Ordinary Least Squares (OLS) as the Lasso, contrary to OLS, does not suffer from overfitting (i.e., the tendency of the in-sample prediction error to go to zero whenever model's complexity increases). This has been rigorously showed by the pioneering paper of Tibshirani (1996). Lasso does not suffer from overfitting as it entails the minimization of a penalized version of the traditional Residual Sum of Squares (RSS), which allows to penalize models with a too abundant set of specified predictors.

By stacking the set of Lasso selected regressors in the column vector $w_{i,t}$ also containing the fixed effects, equation (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. Equation (2) is a partially linear (or partially non-parametric) regression that can be consistently estimated by the so-called "double partalling-out" method provided in Robinson (1986). This procedure allows for estimating non-parametrically the unknown function $m(z_{i,t})$ by obtaining at the same time a root-N consistent estimate of π. The "double partalling-out" procedure goes as follows:

Step 1. Take the expectation of equation (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 equation (3) to equation (1) obtaining:

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

Step 3. Estimate non-parametrically (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 regression of $\hat{r}_{y,it}$ on $\hat{r}_{w,it}$.

Step 4. Once we obtain $\hat{\pi}$ by the previous step, we can use equation (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 equation (5), we can estimate $m(z_{i,t})$ by any possible non-parametric method. In this application, we use a univariate kernel local linear approach as it has good asymptotic properties and 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:

$$\frac{\partial E(Y_{i,t}|z_{i,t})}{\partial z_{i,t}} = m'(z_{i,t}) \quad (6)$$

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

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

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 bootstrap.

4. Empirical results

By carrying out three times the previous procedure, we estimate $m(z_{i,t})$ and $m'(z_{i,t})$ assuming $z_{i,t}$ to be equal to the log of *PO*, *GDP*, and *DEN*. In this way, we can identify the contribution of each driver $z_{i,t}$ to the *EM*, by partialling out the effect of the other drivers. The log transformation allows to account for data heteroskedasticity, and provides parameters in the form of elasticities. We present our results by single *EM* driver.

4.1. The effect of urban population on total greenhouse gas emissions

We start by estimating equation (1) via a Lasso regression to identify the most predictive lag structure for the covariates included in the model. Results are illustrated in Table 1. In this case, we use a 10-fold cross-validation over 88 variables and 1261 observations. The optimal

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

ID	Description	lambda	No. of non-zero coeff.	Out-of-sample R^2	CV mean prediction error
1	first lambda	0.1961	1	0.5421	0.8938
55	lambda before	0.0013	81	0.6915	0.6021
*56	selected lambda	0.0012	83	0.6915	0.6021
57	lambda after	0.0011	84	0.6915	0.6022
61	last lambda	0.0007	86	0.6910	0.6031
No. of CV folds	10	Obs.	1261	No. of covariates	88

Notes: * lambda by Cross-validation. Selection: Cross-validation.

tuning of the model is obtained at a lambda of 0.0012 at which 83 out of 88 predictors are selected, mostly dummy variables related to country and year fixed effects.

Once we have found the best linear specification able to predict the log of *EM*, we run equation (2) over this specification to then estimate *m* (*z*) and *m'*(*x*). Table 2 sets out the results of the linear component of equation (2), where it is evident the significant effect of the first two lags of the log of *EM*, with negative size in both cases smaller than one (remember that coefficients are elasticities). The adjusted R-squared is 0.37 which is of acceptable size.

Table 3 shows the results of the non-parametric estimation of *m(z)* and *m'(z)*, the core of our study. This aims to measure non-parametrically the effect of the log of *PO* on the log of *EM*. We immediately see that the effect is highly significant with a positive elasticity of 0.89 meaning that, when *PO* increases by 10%, *EM* increases by 8.9%. It is a sizable effect, but lower than one, thus signaling low decreasing returns of *EM* to *PO*. The R-squared is rather high as well, around 77%.

Fig. 1 plots the *m(z)* function. As expected, it has a steep curvature pretty close to the 45-degree line of the Cartesian plan. It confirms an elasticity very close to one. Also, the observations' cloud is poorly scattered, thus making this result robust as signaled by the high R-squared commented above.

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. 2, where the red vertical line identifies an elasticity equal to one. We see that only a few observations, less than 10%, show an elasticity larger than one, thus generating a reinforcing effect on *EM*. The large majority presents elasticities smaller than one, in accordance with the overall average effect of Table 3.

Fig. 3, finally, shows the distribution of the prediction of *m(z)*. This distribution is highly symmetric around the mean that, as shown in Tables 3 and is equal to 12.49. As also the range of variation is not too large, we conclude that the predictions of *EM* to different levels of *PO* is rather homogenous, although with some not negligible differences.

4.2. The effect of gross domestic product on total greenhouse gas emissions

Also in this case we start by estimating equation (1) via a Lasso regression to identify the most predictive lag structure for the covariates included in the model. Results are illustrated in Table 4, where we see that the optimal tuning of the model is obtained at a lambda of 0.0010 where 83 out of 88 predictors are selected.

With the best linear specification computed, we can run equation (2) over this specification for then estimating *m*(*z*) and *m'*(*x*). Table 5 sets out the results of the estimation of the linear component of equation (2). Compared to the previous case (the effect of *PO* on *EM*), the current equation is richer in terms of lags components retained by the Lasso. Indeed, it is evident the significant effect of the first two lags of the log of *EM*, with negative elasticity sizes both smaller than one. The adjusted R-squared is 0.37 which is an acceptable size. Besides the significance of lag 1 and 2 of the auto-correlated component of the log of *EM*, other variables and lags are significant: the log of *PO* with an expected positive sign, as well as the lags of this variable; the first lag of the log of *GDP* also shows a negative and significant coefficient. The adjusted R-squared is around 64%, a rather high value.

Table 6 shows the results of the non-parametric estimation of *m(z)* and *m'(z)*, where z is the log of *GDP*. We immediately see that the effect is in this case still highly significant, but with a low and negative average elasticity of −0.12: it means that when the *GDP* increases by 10%, *EM* decreases by 1.2%, a weak effect but at least negative. The R-squared is

Table 2
Partially non-parametric regression results: Effect of *PO* on *EM*.

	Coefficient	[95% Confidence Interval]	
$lnEM_{t-1}$	−0.0475** [0.0231]	−0.0929	−0.0022
$lnEM_{t-2}$	−0.0648** [0.0264]	−0.1166	−0.0129
$lnEM_{t-3}$	0.0006 [0.0237]	−0.0460	0.0471
$lnGDP_{t-1}$	−0.0053 [0.0271]	−0.0586	0.0479
$lnGDP_{t-2}$	0.0046 [0.0316]	−0.0574	0.0667
$lnPO_{t-2}$	0.0001 [0.0393]	−0.0770	0.0772
Obs.	1261	Adj. R^2	0.3781
R^2	0.4008	Root MSE	0.7151

Notes: country and time coefficients are not reported for brevity. [.] denotes Standard Error. ** represents 5% significance level.

Table 3
Non-parametric estimation of *m(z)*.

	Observed Estimate	Percentile [95% Confidence Interval]	
Mean Y	12.4951*** [0.0370]	12.4310	12.5709
Effect lnPO	0.8978*** [0.0178]	0.8621	0.9304
Obs.	1261	E (Kernel obs.)	47
R^2	0.7746	Mean	Effect
Bandwidth	lnPO	0.0373	1.4157

Notes: *** denotes statistical significance at a 1% level. [.] is the Bootstrap Standard Error. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

Fig. 1. Pattern of the kernel local linear estimation of *m(z)*.
Notes: authors' elaborations in STATA.

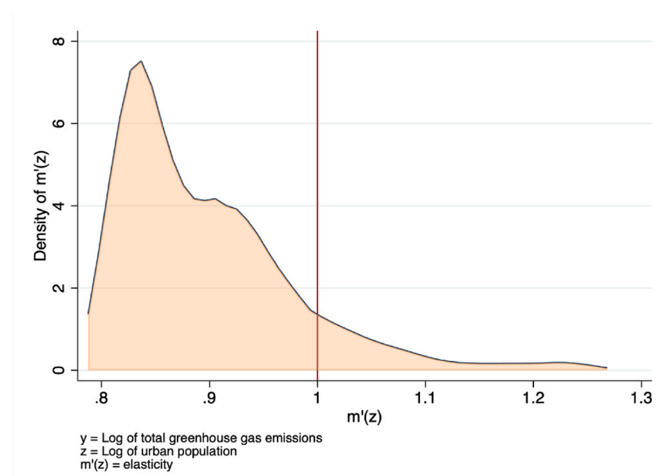

Fig. 2. Distribution of the predicted partial effect *m'(z)*.
Notes: authors' elaborations in STATA.

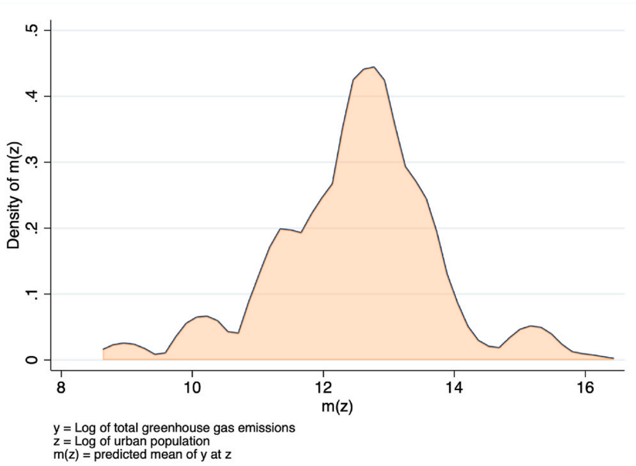

Fig. 3. Distribution of the predicted average *m(z)*.
Notes: authors' elaborations in STATA.

Table 4
Lasso regression results.

ID	Description	lambda	No. of non-zero coef.	Out-of-sample R^2	CV mean prediction error
1	first lambda	0.7308	1	0.1949	1.5714
70	lambda before	0.0012	80	0.6911	0.6029
*71	selected lambda	0.0011	83	0.6912	0.6027
72	lambda after	0.0010	83	0.6912	0.6027
78	last lambda	0.0006	86	0.6907	0.6037
No. of CV folds	10	Obs.	1261	No. of covariates	88

Notes: * lambda by Cross-validation. Selection: Cross-validation.

Table 5
Partially non-parametric regression results.

lnEM	Coefficient	[95% Confidence Interval]	
$lnEM_{t-1}$	−0.0610** [0.0286]	−0.1171	−0.0048
$lnEM_{t-2}$	−0.0726** [0.0290]	−0.1296	−0.0156
$lnEM_{t-3}$	0.0334 [0.0289]	−0.0234	0.0902
lnPO	0.7489*** [0.1856]	0.3847	1.1131
lnDEN	0.1193 [0.1733]	−0.2207	0.4593
$lnPO_{t-1}$	−0.2842* [0.1628]	−0.6035	0.0352
$lnPO_{t-2}$	0.7069*** [0.1666]	0.3799	1.0339
$lnPO_{t-3}$	0.3311** [0.1517]	0.0336	0.6287
$lnDEN_{t-1}$	−0.1874 [0.1720]	−0.5248	0.1500
$lnDEN_{t-2}$	−0.2216 [0.1758]	−0.5665	0.1233
$lnDEN_{t-3}$	0.2905 [0.1933]	−0.0888	0.6698
$lnGDP_{t-1}$	−0.1287** [0.0574]	−0.2412	−0.0161
$lnGDP_{t-2}$	−0.0438 [0.0586]	−0.1589	0.0712
$lnGDP_{t-3}$	0.0581 [0.0485]	−0.0371	0.1533
Obs.	1261	Adj. R^2	0.6481
R^2	0.6721	Root MSE	0.7315

Notes: Country and time coefficients are not reported for brevity. [.] denotes the Standard Error. *, **, *** represent 10, 5, and 1% significance level, respectively.

rather low and around 15%, signaling a large dispersion around the relationship between *EM* and *GDP*.

Fig. 4 plots the *m(z)* function where *z* is the log of *GDP*. As expected, this curve is rather flat with a slight decreasing pattern. This pattern confirms a low and negative elasticity of *EM* to *GDP*. Also, the observations' cloud is now a bit more scattered, thus justifying a lower R-

Table 6
Non-parametric estimation of *m(z)*.

R	Observed Estimate	Percentile [95% Confidence Interval]	
Mean R	12.4915*** [0.0199]	12.4488	12.5220
Effect lnGDP	−0.1262*** [0.0115]	−0.1471	−0.1048
Obs	1261	E (Kernel obs)	175
R^2	0.1585	Mean	Effect
Bandwidth	lnGDP	0.1390	5.0785

Notes: *** denotes statistical significance at a 1% level. [.] is the Bootstrap Standard Error. Parameter estimate using Local-linear regression. Kernel: Epanechnikov; Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

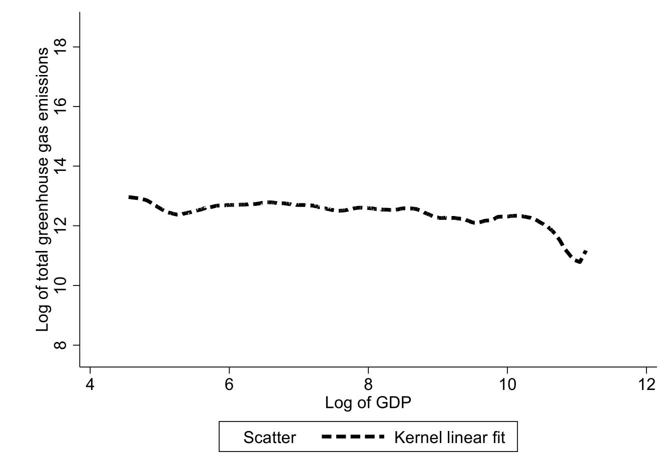

Fig. 4. Pattern of the kernel local linear estimation of *m(z)*.
Notes: authors' elaborations in STATA.

squared as seen above.

The distribution of the effect (i.e., the distribution of *m'(z)*) is visible in Fig. 5, where we immediately see that the elasticities are negative over all the observations. This makes our results on the impact of *GDP* on *EM* quite reliable, as the negative sign of the effect belongs to any observation. Clearly, these negative elasticities are rather uniformly low, ranging from −0.13 to −0.11. We conclude that there is a quite low but homogenous response of *EM* to *GDP*.

Fig. 6, finally, shows the distribution of the predictions of *m(z)*. This distribution is highly right-side asymmetric around the mean (still equal

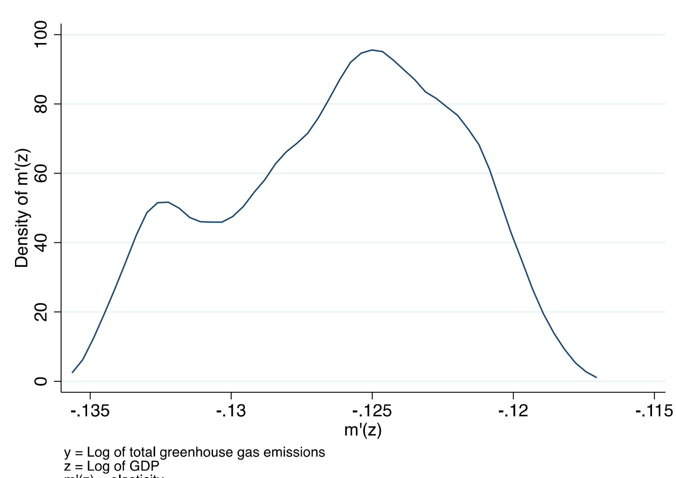

Fig. 5. Distribution of the predicted partial effects *m'(z)*.
Notes: authors' elaborations in STATA.

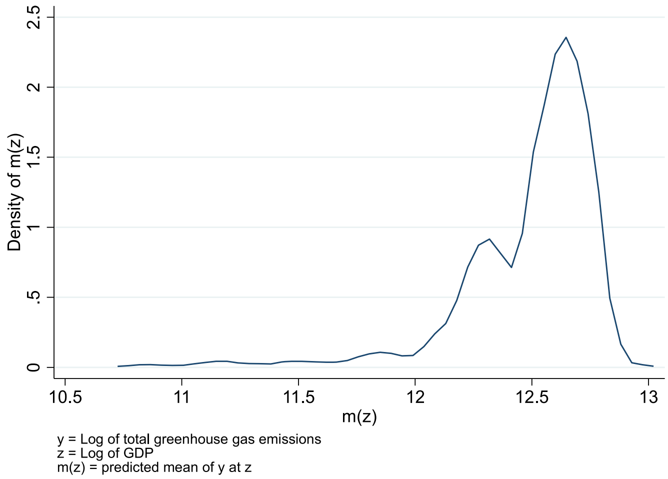

Fig. 6. Distribution of the predicted average effects *m(z)*. Notes: authors' elaborations in STATA.

to 12.49, of course). This means that higher effects are likelier than smaller once. We can also conclude that the predictions of *EM* to different levels of *GDP* is rather heterogeneous.

4.3. *The effect of composite measures of arable, permanent pastures, and cropland on total greenhouse gas emissions*

For the case of the non-parametric relationship between *DEN* and *EM*, Table 7 sets out the estimation of equation (1) by Lasso. The optimal tuning of the model is obtained at a lambda of 0.0023 where 87 out of 88 predictors are selected.

As done for the other two predictors (*PO* and *GDP*), also for *DEN* we run equation (2) over the best specification to then estimate *m(z)* and *m'(x)*. Table 8 sets out the results of the linear component of equation (2), where some lags are significant, and in particular the first and second lag of the log of *EM* with both negative sign; the contemporaneous and second lag of the log of *PO* with both positive sign, the first lag of the log of *GDP*, and the second lag of the log of *DEN*, with both negative sign. The adjusted R-squared is 0.68 which is of acceptable magnitude.

Table 9 shows the results of the non-parametric estimation of m(z) and m'(z), where z is the log of *DEN*. We see that the effect is significant with a positive but small elasticity of 0.19 meaning that, when *DEN* increases of 10%, *EM* increases of 1.9%, a small effect similar to the one found for the *GDP*. The adjusted R-squared is rather low as well, around 16%.

Fig. 7 plots the *m(z)* function and confirms a poor elasticity with high nonlinearity. Moreover, the observations' cloud is poorly scattered, thus making this result fairly robust even although characterized by a low

Table 7
Lasso regression results.

ID	Description	lambda	No. of non-zero coef.	Out-of-sample R^2	CV mean prediction error
1	first lambda	0.9075	1	0.0454	1.8633
89	lambda before	0.0003	86	0.6926	0.5999
*90	selected lambda	0.0002	87	0.6926	0.5999
91	lambda after	0.0002	87	0.6926	0.5999
100	last lambda	0.0001	86	0.6925	0.6002
No. of CV folds	10	Obs.	1261	No. of covariates	88

Notes: * lambda by Cross-validation. Selection: Cross-validation.

Table 8
Partially non-parametric regression results.

	Coefficient	[95% Confidence Interval]	
$lnEM_{t-1}$	−0.0647** [0.0274]	−0.1185	−0.0109
$lnEM_{t-2}$	−0.0958*** [0.0292]	−0.1530	−0.0386
$lnEM_{t-3}$	0.0292 [0.0290]	−0.0276	0.0860
lnPO	1.4494*** [0.1330]	1.1886	1.7103
lnGDP	−0.0264 [0.0563]	−0.1369	0.0840
$lnPO_{t-1}$	−0.1631 [0.1449]	−0.4475	0.1212
$lnPO_{t-2}$	0.4754*** [0.1507]	0.1797	0.7711
$lnPO_{t-3}$	0.1638 [0.1307]	−0.0926	0.4201
$lnGDP_{t-1}$	−0.0878* [0.0458]	−0.1777	0.0021
$lnGDP_{t-2}$	−0.0429 [0.0588]	−0.1582	0.0725
$lnGDP_{t-3}$	0.0528 [0.0486]	−0.0426	0.1483
$lnDEN_{t-1}$	−0.2201 [0.1677]	−0.5491	0.1088
$lnDEN_{t-2}$	−0.3672*** [0.1428]	−0.6474	−0.0870
$lnDEN_{t-3}$	0.3218* [0.1688]	−0.0094	0.6529
Obs	1261	Adj R^2	0.6876
R^2	0.7087	Root MSE	0.7342

Notes: Country and time coefficients are not reported for brevity. [.] denotes Standard Error. *, **, *** represent 10, 5, and 1% significance level, respectively.

Table 9
Non-parametric estimation of *m(z)*.

	Observed Estimate	Percentile [95% Confidence Interval]	
Mean R	12.4934*** [0.0204]	12.4500	12.5306
Effect lnDEN	0.1972*** [0.0362]	0.1018	0.2725
Obs.	1261	E (Kernel obs)	137
R^2	0.1656	Mean	Effect
Bandwidth	lnDEN	0.1087	0.9967

Notes: *** denotes statistical significance at a 1% level. [.] is the Bootstrap Standard Error. Parameter estimate using Local-linear regression. Kernel: Epanechnikov. Bandwidth: Cross-validation. Effect estimates are averages of derivatives.

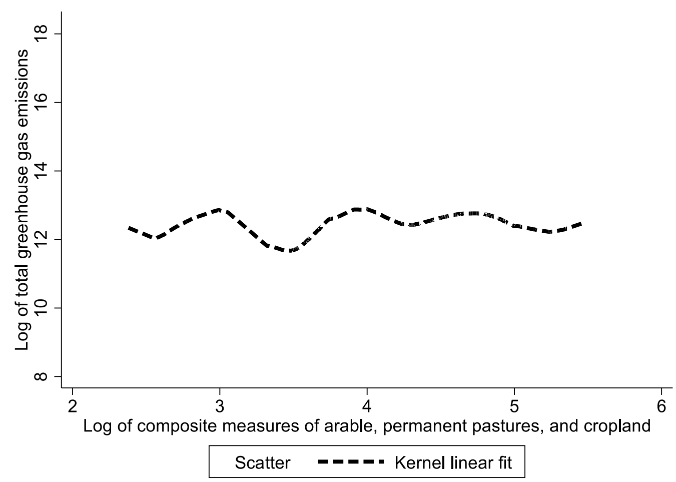

Fig. 7. Pattern of the kernel local linear estimation of *m(z)*.
Notes: authors' elaborations in STATA.

adjusted R-squared.

The empirical distribution of *m'(z)*, the effect of *DEN* on *EM* is visible in Fig. 8. We see that all the observations show a small but positive elasticity. This confirms that, although small, the positive effect is homogenous around the elasticity mean of 0.19.

Fig. 9, finally, shows the distribution of the predicted average of *m (z)*. It is rather skewed and right-side asymmetric. It means that larger positive elasticities are likelier. The range of variation is, however, rather small ranging only from 11.5 to at most 13.

Notes: authors' elaborations in STATA.

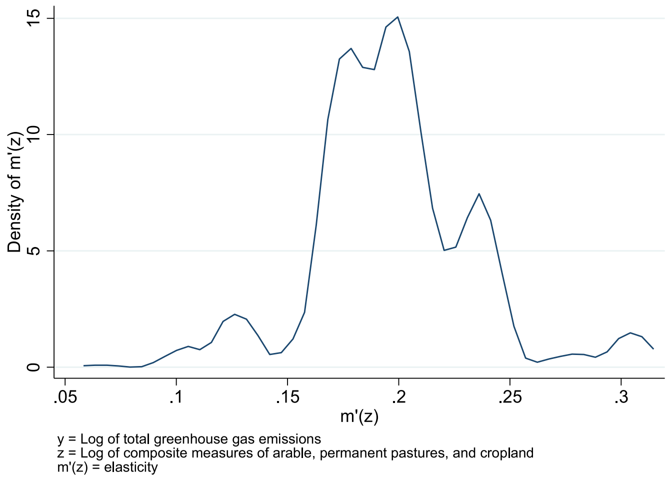

Fig. 8. Distribution of the predicted partial effect *m'(z)*.
Notes: authors' elaborations in STATA.

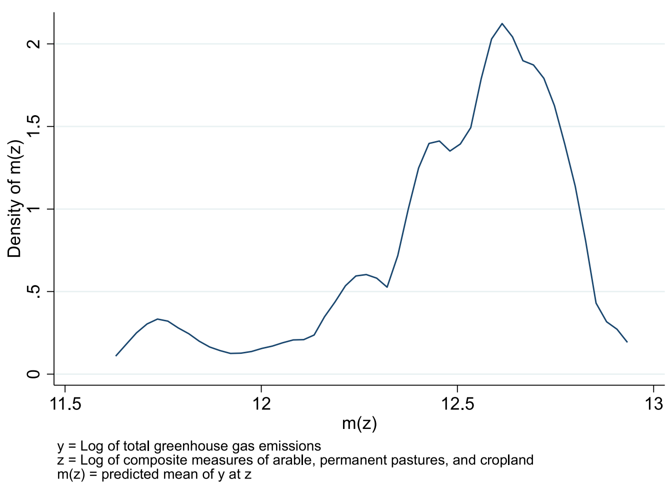

Fig. 9. Distribution of the predicted average *m(z)*.

5. Concluding remarks and policy recommendations

The prime objective of this article is to draw novel conclusions and policies for different income levels of countries regarding the urbanization and agriculture sector land on environmental pollution. In this study, we have considered three important drivers of GHG emissions, that is, urban population, GDP, and a composite measure of arable, permanent pastures, and cropland to catch the agriculture sector's contribution to GHG emissions. In doing so, we employ the data of 50 countries from 1990 to 2019. Notably, we used the maximum available data of countries, and these were further divided into high-income, middle-income, and low-income groups of countries. For empirical analysis, we used the Lasso and non-parametric regression methods. After estimating a Lasso regression to find the best auto-regressive predictive specification, we used an auto-regressive partially linear regression where each of the drivers' effects was modelled non-parametrically. The comprehensive empirical findings allow us to draw novel conclusions and guidelines in line with SDGs. The elasticity effect of the urban population on emissions is significantly positive and sizable, equal to 0.8978. Also, the effect distribution shows a non-negligible share of observations with an elasticity higher than one. Urban population growth is a serious threat to climate change, as it seems to increase sharply CO_2 emissions (although with an elasticity pace smaller than one). The results argue that agglomeration negative effects put in place by larger urban population can partly explain this finding. Agglomeration may however also have the potential to mitigate CO_2 emissions if specialized policies were able to trigger cooperative behaviors able to reduce duplications in energy consumption favoring scale and scope economies in renewable energy-delivering modes. For example, houses' closeness in cities and towns could allow to build and share of solar plants for energy-delivering solutions or can reduce energy waste or misuse. The effects of urbanization growth on GHG emissions in different countries demand urgent attention regarding urbanization policies. In this scenario, collaborations and communication across different income groups and regions should be increased to improve positive urbanization impacts on the environment. In doing, so the countries and regions can also share the policies and adopt the synchronized framework of policies regarding the urbanization processing, resource utilization, and economic repercussions.

The findings of this study are in line with SDG-8: Decent Work and Economic Growth and SDG-12: Responsible Consumption and Production. The elasticity effect of GDP is significantly negative and equal to −0.1262. This is good news, showing that the scale of production, by triggering efficiency, can have a positive effect on emissions reduction. Also, the distribution of the (negative) effects seems quite concentrated around the −0.1262 mean, with no strong effect heterogeneity. The empirical findings argue that economic progress might reduce GHG emissions, this might be due to the use of greener energy sources or other factors. In summary, the conclusions endorse the directions of SDG-2: zero hunger and SDG-13: climate action. The mentioned SDGs are focused on mitigating hunger and pollution globally. To this end, the current study reports the analyses and conclusions for different income groups of countries. The UN SDGs framework strictly focuses on reducing hunger through promoting agriculture and food production activities. Meanwhile, the global organization is keen to reduce environmental externalities such as pollution, temperature change, and climate change challenges.

The elasticity effect of the composite measure is significantly positive but rather small and equal to 0.1972. Larger crop production does seem to represent just a milder threat to climate change. This may be due to an improvement in emission-saving technologies that many farms worldwide have adopted, especially in recent years. Also, the distribution of the (positive) effects seems quite concentrated, with no strong asymmetries. Since urbanization and agriculture sector development not only reinforce each other, but act as a vital engine for economic progress, therefore there is a need for innovative and synchronized reforms for agriculture and urbanization.

The empirical conclusions regarding land use and agricultural land use are novel and allow us to draw some implications. For instance, the governments of low-income and middle-income countries need to promote the awareness level and information for the farmers to adopt climate-friendly resources, farming styles, and modern irrigation tools. In addition, the countries can also introduce some subsidies and public acknowledgment for the farmers and people engaged in agricultural activities. During the absence of regulations for agricultural emissions, personal motivations and acknowledgments can act as a tool for emission mitigation. In addition, the environmental and climate change authorities should enforce the industries and agricultural sector to install treatment plants and follow the environmental regulations and schemes for GHG emissions. Lastly, governments of middle-income and high-income countries can implement sector-specific regulations and taxes depending on the amount of carbon emissions and GHG emissions. In doing so, countries can also introduce some non-economic reforms, which include regulations for forests, trees, water, and arable land. The agricultural reforms might include irrigation and farming techniques such as spin farming, solar tube wells, tunnel farming, technology use agreements, plant double helix, etc.

Caution can be observed while analyzing and implementing the above-mentioned policies, because this study discusses GHG emissions, which are the major contributors to pollution. While future studies can analyze and research the individual components of GHG emissions, and their effects on agricultural and economic factors. Future studies can add nitrogen emissions or sulphur emissions to the empirical analysis, as well as industry-specific pollution and pollutant emissions can be considered to draw more narrow implications. Finally, a novel approach based on ML or Artificial Neural Networks (ANNs) may be used to inspect this topic (Magazzino and Mele, 2022; Mele et al., 2021).

Credit author statement

Cosimo Magazzino: Conceptualization, Validation, Data curation, Supervision, Writing - Reviewing and Editing, Visualization, Giovanni Cerulli: Methodology, Investigation, Software, Umer Shahzad: Writing - Original draft preparation, Salahuddin Khan: Writing - Reviewing and Editing.

Ethical approval

Not applicable.

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. The datasets used during the current study are available from the website and are available on request.

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Appendix

Table A
Descriptive statistics.

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Range	IQR	CV
EM	12.3919	12.4355	1.4368	0.1233	3.0050	7.4941	1.8230	0.1159
PO	16.8298	16.8728	1.2764	0.2357	2.9126	6.4655	1.7001	0.0758
GDP	7.6547	7.4170	1.6253	0.3267	2.0917	6.5753	2.5342	0.2123
DEN	4.3035	4.4535	0.6747	−1.1541	5.2191	5.2203	0.8503	0.1568

Notes: Std. Dev.: Standard Deviation; IQR: Inter-Quartile Range; CV: Coefficient of Variation.
Sources: authors' elaborations.

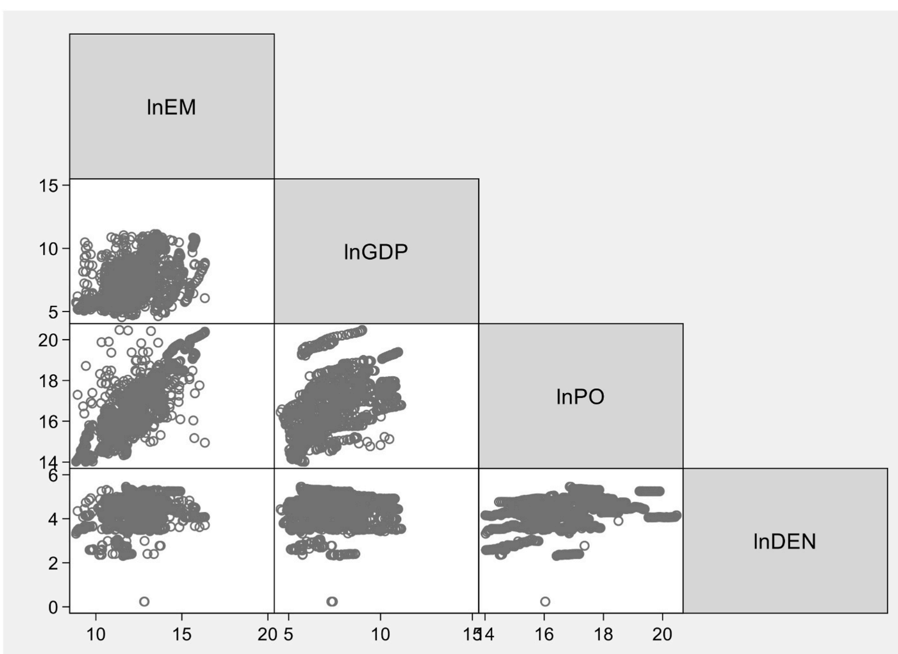

Fig. A. Scatterplot matrices.
Notes: authors' elaborations in STATA.

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