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Analysing the Drivers of Cropland Footprint in Leading Agricultural Nations: Evidence From MMQR Approach

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ABSTRACT

Climate change represents the biggest current challenge for us and for future generations. Its impact on agriculture is undeniable, considering the food security goal. Thus, the cropland footprint has been distinguished as a comprehensive index for assessing the impact of environmental changes in agricultural areas determined by the increased living standards of people and consumption habits. This paper investigates the determinants of the cropland footprint in the top 10 agricultural countries from 1991 to 2021. Among the determinants considered are GDP per capita, urbanisation rate, employment in agriculture, arable land, fertiliser consumption and annual mean temperature. The second-generation panel data analysis technique MMQR was used in the study, after checking for Durbin–Hausman co-integration and the Pesaran CSD test. The results reveal that arable land significantly increases the cropland footprint in higher quantiles (e.g., coefficient = 0.0053 at the 0.90 quantile), while fertiliser consumption shows a significant negative effect across most quantiles (e.g., coefficient = −0.0543 at the 0.30 quantile). Additionally, GDP per capita positively influences the cropland footprint across all quantiles (e.g., coefficient = 0.2138 at the 0.50 quantile). The results from the MMQR analysis suggest that arable land has a significant and positive impact on the cropland footprint in medium and high quantiles. Additionally, fertiliser consumption and GDP per capita demonstrate significant negative and positive impacts, respectively, on the cropland footprint across almost all quantiles. Conversely, urbanisation, annual average temperature and agriculture employment do not significantly impact the cropland footprint. Based on the results, we can state that using fertilisers can help diminish the cropland footprint by increasing the fertility and productivity of the cultivated areas. At the same time, increased GDP per capita and enlarged arable land will increase the cropland footprint. In the context of robust economic growth, fertilisers are important factors to decrease the cropland footprint as a result of using large arable lands for crop purposes.

1 | Introduction

Agricultural production has placed a great burden on the entire ecosystem, causing natural resource waste, biodiversity loss and high carbon emissions (Beyer et al. 2022). Cropland area increased by almost 10% during 2003–2020, especially as the result of agricultural expansion in Africa and South America. Expansion relies on deforestation, and that threatens biodiversity in Latin America, Southeast Asia and Sub-Saharan African countries (Schwarzmueller and Kastner 2022). In Africa, 79% of total cropland expansion occurred at the expense of natural vegetation, while in Southeast Asia, the percentage was 61%, and in South America, it was 39%. In the rest of the world, where agricultural expansion took place some time ago, the current expansion of cropland replaced drylands or previously abandoned arable lands (World Resources Institute 2022). The expansion rate has almost doubled year by year, especially in Africa, while in South America, the annual growth rate has started to decline to nearly half since 2019. 40% of the total African cropland area appeared during the last 20 years to feed a rapidly growing population on this continent (Potapov et al. 2022). However, the expansion of cropland was not caused only by the increased internal demand but also by exports, especially in Southeast Asia and Latin America (Pendrill et al. 2019). While developed countries (plus China and India) made progress lately in increasing their forest areas, deforestation could be noticed in tropical regions (Hoang and Kanemoto 2021). Increased demand for food and other agricultural products (between 35% and 50% from 2010 up to 2050) is due to total population growth rate, urbanisation, increase in income per capita or changes in people's diet structure, and extensive globalisation (van Dijk et al. 2021).

Still, per capita crop decreased during the last decades, from 0.45 ha/capita in 1961 to 0.21 ha per capita in 2016. The lowest value of cropland per capita in the previous decade was in Asia (0.13 ha/capita), Africa (0.22 ha/capita), America and Europe (0.40 ha/capita) and Oceania (1.21 ha/capita). Asia displays the largest share of land equipped for irrigation over cropland (40% in 2016, mainly in China, India, Pakistan and Iran), followed by America (13%, mainly in the United States), Europe (9%), Oceania (7%) and Africa (6%). In absolute terms, India has the largest cropland area, followed by the United States, China and Russia, but this is explained by the large total area of these big countries (FAO-UN 2020).

Total population growth, rapid economic growth rates in some regions and increased standard of living determined a high demand for food and biofuels (Tilman et al. 2011). Balancing the SDGs between ensuring food security, protecting the eco-system and mitigating climate change challenges requires high cooperation at the international level based on independent data and research about agricultural land use and productivity (United Nations 2017).

Cropland is indissolubly related to food production, food security (Yadav and Congalton 2018) and bio-energy (Henry et al. 2018). But changing natural habitat into cropland affects the ecosystem and climate (Usubiaga-Liaño et al. 2019; Marques et al. 2019). That is why cropland is targeted to be limited to 15% of the ice-free land surface (Rockström et al. 2009), which is close to its current value of 14% (Fitzpatrick and Thenkabail 2017). The rest of the agricultural land, around 38% of the total global land surface, is represented by meadows and pastures. This limit of 15% for cropland, among others, is intended for conserving the ecosystem and not determining irreversible climate changes (Rockström et al. 2009). With this limit, it is considered that cropland can support the achievement of SDGs instead of compromising them to preserve biodiversity and losses and the ecosystem. That determined the launch of cropland footprint (CF) as a sustainability ratio (Ridoutt and Navarro Garcia 2020), related to food (Ghosh and Chakma 2019), but also to other bio-economy products (Bruckner et al. 2019). Cropland explains almost 1/3 of the footprint variation (Ridoutt and Navarro Garcia 2020).

Cropland is a scarce resource, and it is usually located near the habitats of people (Thebo et al. 2014). The growing population and rapid urbanisation worldwide will determine the decrease of cropland area by almost 2% between 2000 and 2030, especially in Asia and Africa (Li and Chen 2020). Thus, cropland must be used sustainably to support the achievement of SDGs (Cheng et al. 2020). For crop production, not only should cropland be considered, but also the use of water resources, the use of fertilisers, pesticides and electricity, which implies the use of crop ecological footprint as a ratio for measuring the impact of crop production on the ecosystem, and this ratio is more appropriate than the ecological footprint that is primarily used in many studies (Li et al. 2020).

Among the solutions that have emerged to fight against environmental damage of the extended cropland, some proved to be efficient such as more efficient practices for natural resources management, technological innovations, crops enhanced genetically, use of fertilisers (Springmann et al. 2018), reducing waste and changing food habits, relocating cropland to another area to allow the ecosystem to regenerate (Strassburg et al. 2020), less intensive agricultural and farming systems, and restoring forests and ecosystems where agricultural land has low productivity and cannot be improved. Relocating cropland should alleviate the ecosystem burden but will also diminish the water footprint of agriculture (Beyer et al. 2022) because relocation should be made to areas with sufficient rainfall to skip irrigation (Davis et al. 2017). That is mandatory since the rising temperatures have determined a drop in the productivity of agriculture worldwide (Zhao et al. 2017).

Some studies have proved that the largest CF can be observed in densely populated developed countries where cropland use is restricted by climatic conditions (Marquardt et al. 2019). These countries will drive biodiversity losses and import agricultural products, causing a CF (Chaudhary and Brooks 2019; Shaikh et al. 2021). Bjelle et al. (2021) have shown that with the increase in their income, middle- and low-income economies have faced significant challenges in terms of CF and biodiversity losses. Most affected regions are Latin America, Southeast Asia and sub-Saharan countries, where external trade and exports to developed and developing nations represented the drivers of these biodiversity losses and CF (Marques et al. 2019; Shaikh et al. 2021).

Existing literature focused on determinants of cropland use in some regions, and they have reached various results in regions or applied methods contributing to a more sustainable cropland use. Among the determinants, some studies focused on food security (Santangelo 2018), others on agricultural productivity (Baudron et al. 2015), others on the stage of economic development (Najmuddin et al. 2017), urbanisation (Fu and Weng 2016) or ecosystem challenges (Zhang et al. 2015).

This is the first study that investigates CF concerning both socio-economic and climatic determinants because previous studies analysed these factors separately and their impact on the environment. Most of the earlier studies also focused on the relationship between agriculture and agricultural land and their effects on gas emissions, not on CF (and most of the studies are developed for China, including a recent one which deals with crops and CF). This study combines various determinants of CF in the top 10 agricultural countries worldwide. For these economies relying on agriculture, this analysis is critical for emphasising the impact of socio-economic (economic growth, arable land, fertilisers, urbanisation and employment in agriculture) and climatic factors (temperature) on cropland expansion and how that can affect the ecosystem. That way, authorities can control the socio-economic factors that preserve the ecosystem without causing food security problems, thus addressing some important sustainable development goals. Most of these top 10 agricultural economies are developing countries, and they face many challenges in terms of growing populations, which pose threats to food security and environmental threats caused by the expansion of agriculture, cropland and the reliance on crops. Apart from these specific problems of developing countries, increasing temperature on Earth represents another important issue for countries all over the world, a global challenge that can be addressed only by joint global actions and not the individual actions of one specific country.

This analysis is related to some of the sustainable development goals, namely SDG 2 (Zero Hunger) with SDG 15 (Life on Land) that target to protect, restore and support the sustainable use of land ecosystems, reverse land degradation, prevent desertification, sustainably manage forests and stop biodiversity loss, but ensuring food security at the same time. The most recent UN COP28 Climate Change Conference from 2023 also addressed climate change threats under the Paris Agreement and drew some directions for action up to 2030. The conclusions of the COP28 Conference have shown that progress could have been faster in many areas of climate action, such as decreasing greenhouse gas emissions, improving resilience to climate change and obtaining financial and technological support for less developed and vulnerable economies.

Investigating the CF is important for understanding and managing the environmental impact of food production and consumption in the overall context of growing total global population and a rapid expansion of economic growth worldwide. This is important for settling the sustainability of current agricultural practices, and for supporting the implementation of more sustainable land management policies. The cropland footprint shows where land is not well used and provides information for adopting good practices for sustainable land use such as irrigation, crop rotation and using fertilisers to enhance land productivity. So, it is important to achieve a balance between meeting food demands and diminishing environmental impact.

This research aims to investigate the determinants of CF in the top 10 agricultural countries for 1991–2021 by applying 2nd generation techniques and tests such as MMQR and co-integration tests. Although there are studies investigating cropland, the topic of CF and its determinants was under-investigated in the literature, and this is a critical topic, especially for top agricultural countries to diminish the environmental burden posed by the expansion of cropland and for balancing the achievement of multiple SDGs such as food security, less carbon emissions and preserving the eco-system and natural habitats. This analysis can provide valuable results and policy recommendations for the top 10 agricultural countries on their way to achieving SDGs. Previous research considered a linear and uniform relationship among different factors and CF, while MMQR is used to investigate a heterogeneous impact of these factors on CF across different quantiles, thus it can provide a more comprehensive analysis than considering only the mean. This analysis is also useful when outliers are present. Based on the results of MMQR estimations, policy recommendations can be efficiently tailored.

Section 2 presents important findings of previous studies related to this topic. Section 3 presents data collection and model. Section 4 describes empirical applied methods and results. Section 5 discusses achieved results and Section 6 summarises findings, presents policy implications, limitations and directions for further research.

2 | Literature Review

There are many factors associated with CF and generally with agriculture activity impact on the environment. Economic development represents one of the most significant determinants considering its impact on the environment. Its impact can be either negative if we consider that the economic activity and agriculture are based on natural resources depletion, waste and energy consumption with negative impact on environmental pollution and ecological footprint, or positive if we consider that at certain levels of economic development, technological progress supports ecological activity and ecological agriculture, with positive effects for the environment. Previous research considered as factors for CF the stage of economic development (Najmuddin et al. 2017), urbanisation (Fu and Weng 2016) or ecosystem challenges such as climatic changes (Zhang et al. 2015). Climatic changes exert a great pressure on crops and agriculture because they are largely exposed to weather conditions. Global temperature increases determined drought and the need for large irrigations in agriculture in many regions. That has affected water resources and crops globally. Also, natural hazards have negatively affected agriculture crops. The use of fertilisers in agriculture displays both positive and negative effects on emissions as in previous studies of Guo et al. (2022), Rehman, Ma, et al. (2022), Rehman, Alam, et al. (2022). If their impact on emissions is mixed, fertilisers are good for crops and they increase land productivity, so their association with the CF should be negative. Adedoyin et al. (2020) or Magazzino et al. (2023) investigated the relation between urbanisation and emissions and found a positive association. Urbanisation means decreasing the share of rural areas and of the land that can be used for agriculture. However, the association between crops and urbanization has not been investigated yet. Urbanisation and high pollution can cause decreasing crops and an increase in CF. However, high levels of urbanisation are associated with an increase in economic development and that can also support the productivity in agricultural crops, so it can be associated with a low CF. Raihan et al. (2023) or Shaikh et al. (2024) demonstrated that for economies with a large agricultural sector, more arable land determines the increase in CF such as in Bangladesh and in China because production-based arable land limits were exceeded. Employment in agriculture can also affect crops and CF, depending on the practices and technologies used. Xu et al. (2024) proved a positive correlation between agricultural ecological footprints and factors such as arable land, fertiliser usage and agricultural employment. Still, an increase in labour productivity in agriculture and the usage of clean and modern technologies can mitigate this negative effect of agricultural employment on the environment.

This study focuses on determining the determinants of CF for the top 10 agricultural countries. For this purpose, economic growth, urban population, employment in agriculture, arable lands, fertiliser consumption and annual mean temperature were considered potential determinants, and empirical analyses were carried out within this framework. This section aims to examine existing studies in the literature within the framework of the relevant model. Accordingly, the studies in the literature were compiled and reported in Table 1. When Table 1 is examined, it is seen that most of the studies focus on only one or a few of the variables that are the focus of this study. For example, it is understood that most of the studies were carried out within the framework of urbanisation, agriculture, GHG and CO_2 variables. As examples of these studies, Wang and Su (2019), Adedoyin et al. (2020), and Magazzino et al. (2023) examine the effects of urbanisation on carbon emissions. According to the general conclusion of these studies using different countries, methods and periods, urbanisation increases CO_2. Smolski and Clark (2024) examined the cropland expansionary dynamics of agricultural production in Latin America from 1970 to 2016. They concluded that trade direction and export orientation positively correlate with CF.On the other hand, Ben Jebli and Ben Youssef (2019) reported that agricultural production for Brazil, Bas et al. (2021) of agricultural added value for Türkiye, and Kara et al. (2022) also concluded that agricultural land suitable for arable agriculture reduces CO_2 for Türkiye. On the other hand, Si et al. (2021) found that agriculture causes CO_2 in China, and Raihan et al. (2023) concluded that agricultural land increases GHG in Bangladesh. When the literature is examined in the context of economic growth, Rehman et al. (2020) concluded that CO_2 has a positive and significant relationship with agricultural GDP for China. Again, for China, Koondhar, Tan, et al. (2021) reported that CO_2 had a significant and negative relationship with agricultural bioeconomic growth. Shaikh et al. (2024) investigated China's CF, and they concluded that 86% of China's arable land footprint originates in regions that exceed production-based arable land limits. In general, it can be seen that studies conducted for China predominate in the literature.

When the empirical literature is generally evaluated, it is seen that there is no study focusing on the CF. Only one recent study focuses on the CF in China but in relation to population growth, dietary preferences and the productivity of technologies used in agriculture. In general, it has been observed that studies in which CO_2 and GHG are environmental indicators predominate. Moreover, if we check the results of previous studies presented above, we can see mixed results for the impact of agriculture on emissions or for the effects of fertilisers on the environment, depending on the country, period of investigation and research method. In particular, examining the effects of agriculture and its components on the environment using the CF, which is also a specific environmental indicator, is of great importance in terms of the reliability of the results, the determination of the simple effects, and the positive results of the policies to be recommended accordingly. Again, many CF determinants have yet to be included in the literature. This study aims to produce solid results based on the most comprehensive model which includes social factors (urbanisation, employment in agriculture), climatic factors (temperature increase) and economic factors (arable land, fertilisers, GDP growth). All these determinants influence crops and affect the CF and thus the environment. Given all these explanations, this study is likely to fill an essential gap in the literature.

3 | Data and Model

This study investigates the determinants of CF in the top 10 agricultural countries from 1991 to 2021. For this aim, we use the CF as the dependent variable and arable land measured as % of land area (ARB), fertiliser consumption measured as kilograms per hectare of arable land (LNFERT), and employment in agriculture as % of total employment modelled by International Labor Organization estimate (EMP) as regressors. We also use gross domestic product per capita in constant 2015 US Dollar prices (GDP), urban population as % of total population (URB), and annual mean temperature (TEMP) as control variables. The sample consists of the top 10 agricultural countries globally—namely China, India, the United States, Brazil, Indonesia, Nigeria, Turkey, Japan, Argentina and Thailand—selected based on their total agricultural output and their influence on global food production and trade. This selection enables the study to focus on countries that play a critical role in both global agricultural dynamics and environmental sustainability. The period 1991–2021 was chosen to ensure sufficient temporal coverage for long-term analysis and because reliable and consistent data for the selected indicators are available across this time frame. Table 2 shows the details and sources of the selected variables employed in the empirical analysis. All data used in this study were collected from reputable and publicly accessible international sources to ensure consistency and comparability. The CF data were obtained from the Global Footprint Network (2021), while all socio-economic and climatic variables were sourced from the World Bank Open Data platform (2024). These databases are widely used in empirical environmental and economic research. However, some limitations should be noted. First, data availability restricted the analysis to the 1991–2021 period and the selected 10 countries. Second, missing observations were excluded to construct a balanced panel, which may slightly reduce country-year representation. Third, while the data sources are considered reliable, reporting and measurement differences across countries could still affect accuracy. Nevertheless, log transformations and standardised units were applied to mitigate skewness and improve consistency.

Detailed data sources and variable definitions are listed in Table 2.

The data for CF are gathered from the Global Footprint Network. GDP, URB, EMP, ARL, FERT and TEMP are obtained from the World Bank. We use GDP and FERT in logarithmic forms for empirical purposes. Table 3 reports the descriptive statistics analysis of all the series.

In econometric studies, graphical analyses of variables that should be presented before analyses are performed (Figure 1).

TABLE 1 | Summary of the related studies in the literature.

Author(s)	Countries	Period	Methods	Results
Wang and Su (2019)	China	1990–2015	Time Series Analyses	URB increases CO_2.
Ben Jebli and Ben Youssef (2019)	Brazil	1980–2013	Time Series Analyses	Agricultural production reduces CO_2.
Bruckner et al. (2019)	EU	1995–2010	Landflow model	Cropland footprint from non-food products in Europe is determined by imports from China, the United States and Indonesia.
Niu et al. (2020)	151 Countries	2016	Quasi-input–output analysis	Mixed results from land use.
Rehman et al. (2020)	China	1978–2017	ARDL	CO_2 has a significant and positive relationship with agricultural GDP.
Adedoyin et al. (2020)	Sub-Saharan African countries	1980–2014	PMG-ARDL	URB increases CO_2.
Bas et al. (2021)	Turkey	1991–2019	FMOLS-CCR	Agriculture value-added reduces CO_2.
Koondhar, Tan, et al. (2021)	China	1971–2019	Dynamic ARDL	CO_2 has a significant and negative nexus with agricultural bioeconomic growth.
Koondhar, Udemba, et al. (2021)	Pakistan	1976–2018	Nonlinear ARDL	Agricultural carbon emission has a significant effect on cereal food production.
Si et al. (2021)	China	1990–2012	VECM Model	Agriculture causes CO_2.
Kara et al. (2022)	Turkey	1988–2019	ARDL	Agricultural land for arable farming reduces CO_2.
Rehman, Ma, et al. (2022)	Nepal	1965–2018	Asymmetric NARDL	Fertiliser consumption increases CO_2.
Rehman, Alam, et al. (2022)	Bhutan	1980–2020	ARDL	Fertiliser consumption decreases CO_2.
Baig et al. (2023)	India	1991–2018	ARDL	CO_2 harms Agriculture.
Guo et al. (2022)	30 provinces in China	2000–2019	Panel Data Analyses	Chemical fertiliser consumption positively impacts carbon emissions.
Yang et al. (2022)	China	2000–2019	FMOLS, DOLS, ARDL	During rainfalls, agricultural carbon emissions increase, during sunlight agricultural carbon emissions decrease. Climate impact on agriculture emissions differs.
Guotong et al. (2022)	China	2001–2020	Carbon sequestration model	The carbon sink capacity of Guangdong farms ecosystems showed an overall decreasing trend, but carbon footprint decreased. Nitrogen fertilisers were the main polluters.
Magazzino and Santeramo (2023)	130 Economies	1991–2019	Panel VAR Model	Mixed results for agriculture.

(Continues)

TABLE 1 | (Continued)

Author(s)	Countries	Period	Methods	Results
Raihan et al. (2023)	Bangladesh	1990–2018	ARDL	Agricultural land increases GHG.
Magazzino et al. (2023)	50 Economies	1990–2019	Panel Regressions	URB increases CO_2.
Ma et al. (2024)	Top eight agricultural emitters	1990–2020	Dynamic Panel Data Analyses	Fertiliser consumption increases GHG
Zhang et al. (2024)	China	1987–2013	Data Analysis	Concentrating feed crops increases cropland footprint.
Li et al. (2024)	China	2000–2021	Spatial Autoregressive Model	The non-grain production of cropland increases carbon emission intensity.
Xu et al. (2024)	China	1990–2020	ARDL model	Positive association between arable land, fertilisers, employment in agriculture and agriculture ecological footprint.
Wang et al. (2024)	China	2011–2021	Standard deviation ellipse, Tapio decoupling theory, Markov chain	Agriculture ecosystem in the middle and lower districts of the Yangtze River significantly acted as a carbon sink.
Pan et al. (2025)	Chinese Provinces	1980–2020	Three-dimensional ecological footprint; spatio-temporal pattern	Cropland impacts on ecological footprint following an inverted N-shape pattern, with regional disparities. Fertilisers increase carbon emissions.
Kong and Li (2025)	China	2013–2022	Carbon sequestration model	Carbon emissions decreased. Fertiliser and irrigated agriculture produced more carbon emissions. Fluctuations of carbon footprint decreased. Cropland ecosystems displayed carbon reduction. Temperature indirectly impacts on carbon sequestration and carbon emissions from crops.

This allows for the observation of hypothetical fluctuations and changes in variables within the defined period, leading to possible interpretations. Upon examining the variables, it becomes evident that their values fluctuate across countries over time. Except for the TEMP variable, most variables display a broader distribution. Some variables reach peak levels in certain countries, whereas in others, they remain considerably low.

Table 3 presents summary statistics for all variables used in the analysis. The high standard deviations of EMP and ARL indicate substantial variation across countries, while the relatively low mean of the CF reflects the limited availability of agricultural land on a per capita basis. The mean values of CF, ARL, EMP, LNFERT, LNGDP, TEMP and URB are 0.588, 22.787, 28.293, 4.625, 8.740, 0.779 and 60.590, respectively. The descriptive statistics also report all variables' median, minimum and maximum values. We estimate the following empirical model:

$$\begin{aligned} \mathrm{CF}_{it} = \; & \beta_{it} + \beta_1 \mathrm{ARB}_{it} + \beta_2 \mathrm{LNFRT}_{it} + \beta_3 \mathrm{EMP}_{it} \\ & + \beta_4 \mathrm{GDP}_{it} + \beta_5 \mathrm{URB}_{it} + \beta_6 \mathrm{TEMP}_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where $i = 1, 2, 3, \ldots N$ denotes cross-section data, $t = 1, 2, 3, \ldots T$ is the time dimension and ε reflects the error term.

The construction of the empirical model is grounded in the Environmental Kuznets Curve (EKC) hypothesis and the theory of sustainable land use, both of which highlight the complex interactions between economic development, resource utilisation and environmental degradation. Accordingly, the selected variables—GDP per capita, urban population, fertiliser consumption, arable land, employment in agriculture and mean annual temperature—are widely recognised in the literature as key drivers of environmental pressure, particularly in the context of agricultural land use. The log-linear form applied to GDP and fertiliser consumption addresses potential skewness in the data and enables the interpretation of coefficients as elasticities, which enhances the explanatory power and comparability of the model with previous studies in environmental economics.

The theoretical framework of the estimation model (Equation 1) is based on the relationship between CF and several socio-economic and climatic factors. CF is the dependent variable and is defined as the amount of land required to produce the food and fibre consumed by a given population. It measures the environmental impact of agriculture. ARL is the percentage of land area that is suitable for growing crops. It is expected to positively impact the CF, as more arable land

TABLE 2 | Variables of the analysis.

Variable	Explanation	Source
CF	Cropland Footprint (gha per person)	Global Footprint Network (2021)
LNGDP	GDP per capita (constant 2015 US$)	World Bank (2024)
URB	Urban population (% of total population)	World Bank (2024)
EMP	Employment in agriculture (% of total employment) (modelled ILO estimate)	World Bank (2024)
ARL	Arable land (% of land area)	World Bank (2024)
LNFERT	Fertiliser consumption (kilograms per hectare of arable land)	World Bank (2024)
TEMP	Annual mean temperature	World Bank (2024)

TABLE 3 | Descriptive statistics.

	CF	ARL	EMP	LNFERT	LNGDP	TEMP	URB
Mean	0.588938	22.78708	28.29359	4.625451	8.740302	0.779632	60.59073
Median	0.464948	16.18439	31.00955	4.850165	8.750511	0.758500	60.78650
Maximum	1.526751	54.88448	63.40898	6.174290	11.03214	2.596000	92.22900
Minimum	0.042659	5.092401	1.575147	1.422528	6.270796	−1.258000	25.77800
Std. Dev.	0.333667	14.58514	19.25426	1.102685	1.208934	0.470751	22.51161
Skewness	0.990625	0.799614	0.031008	−1.245296	0.182769	0.120212	−0.062043
Kurtosis	3.010593	2.459201	1.570212	4.093601	2.205531	4.633087	1.448368
Jarque–Bera	50.70395	36.81239	26.45513	95.57061	9.878663	35.19504	31.29654
Probability	0.000000	0.000000	0.000002	0.000000	0.007159	0.000000	0.000000
Sum	182.5709	7063.996	8771.014	1433.890	2709.494	241.6860	18783.13
Sum Sq. Dev.	34.40209	65732.43	114554.5	375.7172	451.6100	68.47630	156592.7
Observations	310	310	310	310	310	310	310

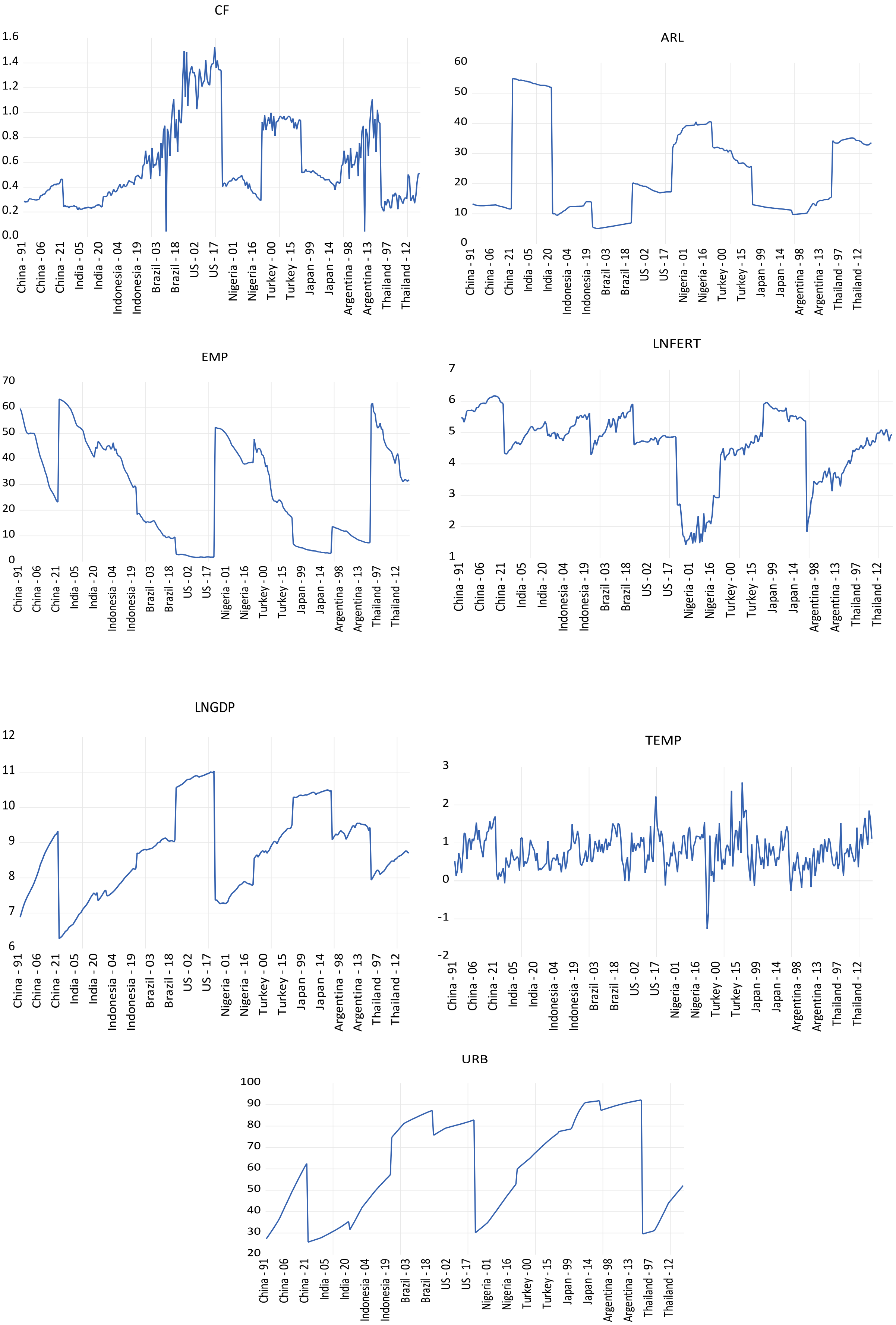

FIGURE 1 | The distribution of the data belonging to the variables by countries and years.

means more land available for agriculture, which could lead to increased production and consumption of agricultural products (Kara et al. 2022; Raihan et al. 2023). LNFERT is a logarithmic measure of fertiliser used per hectare of arable land. It is expected to negatively impact the CF, as increased fertiliser use can lead to increased crop yields, reducing the amount of land needed to produce a given amount of food (Ma et al. 2024; Rehman, Alam, et al. (2022)). EMP is the percentage of the total workforce employed in agriculture. It is expected to positively impact the CF, as more people working in agriculture could lead to increased agricultural production and consumption. LNGDP is a logarithmic measure of a country's economic output per person. It is expected to positively impact the CF, as higher incomes are often associated with increased consumption of agricultural products (Rehman et al. 2020). URB is the percentage of the total population living in urban areas. Urbanisation can lead to the conversion of agricultural land to urban uses, which is expected to impact the CF negatively (Adedoyin et al. 2020). TEMP is the average temperature over a year. It is expected to have a negative impact on the CF, as higher temperatures can lead to reduced crop yields, increasing the amount of land needed to produce a given amount of food.

The model is estimated using the method of moments quantile regression (MMQR), which allows for the estimation of the impact of the explanatory variables on the CF at different quantiles of the distribution. This is important because the impact of the explanatory variables may vary depending on the level of the CF.

The empirical model is specified based on the theoretical framework linking socio-economic and climatic variables to CF, in line with the Environmental Kuznets Curve (EKC) and sustainable land use theory. All independent variables were selected based on prior literature and theoretical relevance. The model includes GDP per capita (log-transformed), urbanisation, employment in agriculture, arable land, fertiliser use (log-transformed) and annual mean temperature as regressors.

To ensure robustness of the findings, several steps were taken:

- Cross-sectional dependence (CSD) and slope heterogeneity were tested using second-generation panel diagnostics (e.g., Pesaran CD test, Delta test).
- Stationarity was confirmed using PANIC unit root tests, and co-integration was tested using the Durbin–Hausman approach.
- MMQR was applied across quantiles to capture heterogeneity in effects.
- In addition to panel-level results, country-level interpretations were provided where feasible, based on datasets, to validate consistency across different contexts.

These methodological choices aim to ensure that the model is well-specified, data-driven and yields robust policy-relevant insights.

4 | Methodology and Empirical Results

4.1 | Cross-Sectional Dependence and Homogeneity Tests

Several pivotal preliminary conditions should be tested in the panel data analysis, including cross-sectional dependence and country-specific coefficient homogeneity. One of the widely employed tests in the literature to ascertain coefficient homogeneity is the Delta ($\tilde{\Delta}$) test developed by Pesaran and Yamagata (2008). This test rigorously examines the null hypothesis of coefficient homogeneity against the alternative hypothesis positing coefficient heterogeneity. The assessment of cross-sectional dependence seeks to determine whether shocks occurring in one unit, integrated within the panel, exert an influence on other units. Within this context, the LM test devised by Breusch and Pagan (1980), the CDLM and CD tests by Pesaran (2004), and the LM_{adj} test advanced by Pesaran et al. (2008) are frequently enlisted in panel data analysis. Tables 4 and 5 show the results of cross-sectional dependence and homogeneity (Delta Test) results, respectively.

The test results in Table 4 confirm significant cross-sectional dependence among all variables, indicating that shocks in one country are likely to affect others in the panel. This justifies the use of second-generation panel econometric techniques. In Table 4, we have strong evidence to reject the null hypothesis of cross-sectional independence for all analysed variables. In other words, all variables have cross-sectional dependence.

The rejection of slope homogeneity in Table 5 suggests that relationships between variables vary across countries, reinforcing the use of quantile regression, which captures heterogeneous effects. The Delta test results reject the null hypothesis that there is slope homogeneity among the variables. The results indicate the heterogeneity of the slopes.

4.2 | Panel Unit Root Test

The PANIC unit root test, which considers cross-sectional dependence, has been utilised to ascertain whether the variables in the model contain unit roots, representing one of the second-generation unit root tests. The test developed by Bai and Ng (2004, 2010) investigates the presence of a unit root by separately examining the common factor and idiosyncratic components. The null hypothesis H_0 of the test suggests that the variable contains a unit root, whereas the alternative hypothesis H_1 suggests that the variable does not contain a unit root. Table 6 displays the PANIC unit root test results with constant and constant and trend specifications (Pesaran 2007).

Most variables are non-stationary at level but become stationary at first difference, supporting the need for co-integration analysis. TEMP is an exception, being stationary at level under certain specifications. We find that all variables are not stationary at their levels except TEMP. However, they are stationary processes at their first differences both in constant and constant and trend specifications since we have enough evidence to reject the null hypothesis of the unit root. Since all variables have the order of integration at first differences, one can investigate via

TABLE 4 | Results of cross-section dependence test.

Variables	CD test	CD_{lm1} (Breusch and Pagan 1980)	CD_{lm2} (Pesaran 2004)	CD (Pesaran 2004)	LM_{adj} (Pesaran and Yamagata 2008)
CF	Test Statistic	323.0590*	29.3099*	0.4737	29.1433*
	P-value	0.0000	0.0000	0.6357	0.0000
ARL	Test Statistic	892.4952*	89.3338*	−2.2870**	89.1671*
	P-value	0.0000	0.0000	0.0222	0.0000
EMP	Test Statistic	1200.938*	121.8465*	34.5558*	121.6799*
	P-value	0.0000	0.0000	0.0000	0.0000
LNFERT	Test Statistic	725.3116*	71.7111*	14.4709*	71.5444*
	P-value	0.0000	0.0000	0.0000	0.0000
LNGDP	Test Statistic	1178.893*	119.5228*	34.2548*	119.3561*
	P-value	0.0000	0.0000	0.0000	0.0000
TEMP	Test Statistic	547.8700*	53.0071*	22.8603*	52.8404*
	P-value	0.0000	0.0000	0.0000	0.0000
URB	Test Statistic	1327.726*	135.5112*	36.4295*	135.0444*
	P-value	0.0000	0.0000	0.0000	0.0000

Note: * indicates that there is a long-run relationship between the variables at a 1% significance level.

TABLE 5 | Results of the homogeneity test.

Test statistic	Statistic value	*p*
Delta_tilde	7.041*	0.0000
Delta_tilde_adj	8.130*	0.0000

Note: * indicates that there is a long-run relationship between the variables at a 1% significance level.

a co-integration test whether the variables of the model are co-integrated in the long run.

4.3 | Co-Integration Test

The stationary behaviour of the dependent variable in first differences, along with identifying the level or first-difference stationarity of explanatory variables, facilitates the examination of the potential long-term relationship among variables. To examine the existence of a long-term relationship among variables, the Durbin–Hausman panel co-integration test developed by Westerlund (2008), which takes into account cross-sectional dependence, has been utilised. Comprising two distinct tests—group statistics and panel statistics—the Durbin–Hausman test was selected for its consideration of cross-sectional dependence. In the Durbin–Hausman panel co-integration test, the null hypothesis indicating no co-integration is tested against the alternative hypothesis asserting the presence of co-integration.

Table 7 provides the D-H panel co-integration test results. According to the results of the Durbin-H test of co-integration obtained from group and panel statistics, the null hypothesis is rejected. In other words, Durbin–Hausman panel co-integration test results indicate there is a long-term relationship between the response variable (CF) and explanatory variables. The significant results of the Durbin-H test indicate the existence of a long-run equilibrium relationship among the variables, validating the estimation of a long-run model like MMQR.

4.4 | Methods of Moments Quantile Regression (MM-QR) Estimation

Quantile regression analysis enables coefficient estimation for all quantiles by establishing a relationship between the conditional quantiles of the dependent variable and the explanatory variables. This method yields more robust and effective coefficient estimates compared to other estimation methods when the variables deviate from a normal distribution. This method was proposed in the seminal paper of Koenker and Bassett Jr. (1978). Machado and Silva (2019) discuss the conditions for estimating regression quantiles by estimating conditional means, highlighting the advantage of this approach in allowing the utilisation of methods valid only for conditional means estimation while still providing insights into regressor effects on the entire conditional distribution. This is provided by the insight they use to estimate quantiles from estimates of the conditional mean and the conditional scale function. This method offers a straightforward means to approximate regression quantiles in scenarios where employing the conventional method proves challenging. The aim of the research is to examine the effects of factors affecting CF at different levels. MMQR allows for the analysis of variables' effect on average values and at different quantiles (low, medium, high).

TABLE 6 | PANIC unit root test results.

Variables	Statistic	Constant			Constant and trend		
		Pa	Pb	PSMB	Pa	Pb	PSMB
CF	Test Statistic	−1.278	−0.700	−0.871	−2.99*	−1.941**	−1.044
	p	0.1005	0.242	0.1918	0.0014	0.0261	0.1483
ΔCF	Test Statistic	−36.301*	−7.646*	−1.286***	−20.488*	−8.37*	−1.413***
	p	0.0000	0.0000	0.0992	0.0000	0.0000	0.0788
ARL	Test Statistic	−0.097	−0.09	−0.138	−0.065	−0.064	−0.076
	p	0.4613	0.464	0.4452	0.474	0.4745	0.4698
ΔARL	Test Statistic	−13.558*	−4.602*	−1.674**	−8.597*	−4.247*	−1.607***
	p	0.0000	0.0000	0.047	0.0000	0.0000	0.0541
EMP	Test Statistic	−2.399*	−1.595***	−1.08	−0.187	−0.181	−0.166
	p	0.0082	0.0553	0.140	0.4257	0.4282	0.4342
ΔEMP	Test Statistic	−20.648*	−5.963*	−1.659**	−14.799*	−6.519*	−2.041**
	p	0.0000	0.0000	0.0486	0.0000	0.0000	0.0206
LNFERT	Test Statistic	1.133	1.347	1.277	−1.646**	−1.367***	−0.945
	p	0.8715	0.9111	0.8992	0.0498	0.0858	0.1723
ΔLNFERT	Test Statistic	−34.959*	−8.982*	−1.941**	−23.397*	−9.279*	−2.133**
	p	0.0000	0.0000	0.0261	0.0000	0.0000	0.0165
LNGDP	Test Statistic	−1.284***	−1.011	−0.723	0.477	0.532	0.567
	p	0.0995	0.1561	0.2348	0.6834	0.7025	0.7148
ΔLNGDP	Test Statistic	−18.348*	−6.177*	−2.063**	−13.54*	−6.622*	−2.348*
	p	0.0000	0.0000	0.0196	0.0000	0.0000	0.0094
TEMP	Test Statistic	−11.46*	−4.505*	−1.939**	−15.204*	−7.337*	−2.409*
	p	0.0000	0.0000	0.0263	0.0000	0.0000	0.008
ΔTEMP	Test Statistic	−16.559*	−5.131*	−1.412***	−18.265*	−7.618*	−1.891**
	p	0.0000	0.0000	0.079	0.0000	0.0000	0.0293
URB	Test Statistic	1.118	1.889	4.099	1.001	1.264	1.561
	p	0.8691	0.9705	0.9985	0.8417	0.8969	0.9408
ΔURB	Test Statistic	4.159*	5.975*	1.821***	8.334*	9.192*	2.455**
	p	0.0000	0.0000	0.085	0.0000	0.0000	0.0462

Note: *, ** and *** indicate that the coefficients are significant at the 1%, 5% and 10% levels, respectively.

TABLE 7 | Durbin–Hausman co-integration test results.

Test statistic	Statistic value	*p*
Durbin-H Group Statistic	1161.827*	0.000
Durbin-H Panel Statistic	18.344*	0.000

Note: * indicates that there is a long-run relationship between the variables at a 1% significance level.

In this way, the effect of factors such as income level, fertiliser use, or arable land on the CF can be examined in more detail under different economic and social conditions.

This approach follows the methodology proposed by Koenker and Bassett Jr. (1978) and further extended by Machado and Silva (2019), which allows for robust inference across different conditional quantiles. For robustness, preliminary tests such as cross-sectional dependence (Pesaran 2004), slope heterogeneity (Pesaran and Yamagata 2008), unit roots (Bai and Ng 2004) and co-integration (Westerlund 2008) were carefully conducted in line with second-generation panel data analysis practices.

Table 8 shows the results of the MMQR model.

Table 8 shows the effect of explanatory variables on CF at low, medium and high levels through the MMQR test. Arable land

TABLE 8 | MMQR results.

	Variables	ARL	EMP	LNFERT	LNGDP	TEMP	URB	Constant
	Location	0.0025** (0.016)	0.0028 (0.587)	−0.0460* (0.001)	0.1933* (0.000)	0.0143 (0.764)	0.0043** (0.034)	−1.2981** (0.034)
	Scale	0.0018** (0.011)	0.0046 (0.197)	0.0110 (0.246)	0.1139* (0.000)	−0.0118 (0.721)	0.0027 (0.263)	−1.2019* (0.005)
Quantiles	0.10	0.0002 (0.981)	−0.0034 (0.445)	−0.0609* (0.000)	0.0388 (0.307)	0.0304 (0.470)	0.0005 (0.862)	0.3312 (0.530)
	0.20	0.0006 (0.431)	−0.0018 (0.660)	−0.0571* (0.0000)	0.0785 (0.029)**	0.0262 (0.500)	0.0015 (0.604)	−0.0876 (0.859)
	0.30	0.0011 (0.188)	−0.0006 (0.869)	−0.0543* (0.000)	0.1072* (0.004)	0.0233 (0.548)	0.0022 (0.446)	−0.3897 (0.438)
	0.40	0.0018** (0.049)	0.0011 (0.802)	−0.0499* (0.000)	0.1523* (0.000)	0.0186 (0.657)	0.0033 (0.293)	−0.8663 (0.118)
	0.50	0.0028** (0.012)	0.0036 (0.515)	−0.0440* (0.003)	0.2138* (0.000)	0.0122 (0.812)	0.0048 (0.214)	−1.5149** (0.022)
	0.60	0.0036* (0.006)	0.0057 (0.397)	−0.0391** (0.028)	0.2648* (0.000)	0.0069 (0.911)	0.0060 (0.195)	−2.0524* (0.009)
	0.70	0.0041* (0.005)	0.0068 (0.357)	−0.0363*** (0.064)	0.2928* (0.000)	0.0040 (0.953)	0.0067 (0.192)	−2.3481* (0.006)
	0.80	0.0045* (0.004)	0.0079 (0.330)	−0.0338 (0.116)	0.3193* (0.000)	0.0012 (0.986)	0.0073 (0.191)	−2.6272* (0.005)
	0.90	0.0053* (0.006)	0.0099 (0.300)	−0.0290 (0.250)	0.3683* (0.000)	−0.0038 (0.965)	0.0085 (0.195)	−3.1450* (0.006)

Note: *, ** and *** indicate that the coefficients are significant at 1%, 5% and 10% levels, respectively.

(ARL) positively affects CF in medium and high quantiles, indicating that land expansion worsens environmental outcomes in high-impact countries. Fertiliser use (LNFERT) shows a consistent negative effect across quantiles, suggesting productivity gains reduce land pressure. GDP per capita (LNGDP) has a significant and positive effect, reflecting consumption-driven land use pressure.

The LNFERT variable was found to have a negative and statistically significant effect on CF at low, medium and high-level quantiles (0.10–0.20–0.30–0.40–0.50–0.60–0.70). Therefore, an increase in fertiliser consumption is associated with a decrease in environmental pollution measured by CF. Accordingly, using fertilisers can help diminish the CF by increasing the fertility and productivity of the cultivated areas. The negative effect of fertiliser consumption on CF can be interpreted as fertiliser increasing soil fertility and allowing less land to be used to produce the same level of crops, thus reducing the amount of land needed per unit of production. This suggests that fertiliser use can play an important role in sustainable agricultural practices and be an effective tool in reducing environmental impact. Our findings on the effect of fertiliser consumption on CF are consistent with those of Rehman, Alam, et al. (2022) but contradict those of Rehman, Ma, et al. (2022). However, Rehman, Ma, et al. (2022) and Rehman, Alam, et al. (2022) used CO_2 as an indicator of environmental pollution.

The ARL variable is found to have a positive and statistically significant effect on CF at medium and high-level quantiles (0.40–0.50–0.60–0.70–0.80–0.90). Accordingly, an increase in the percentage of arable lands in the total land area in the studied countries is associated with an increase in CF. The positive effect of arable land amount on CF can be explained by the fact that opening up more land for agricultural production leads to the conversion of natural habitats into agricultural land, resulting in negative environmental consequences such as biodiversity loss and habitat destruction. Furthermore, increased land use can lead to increased use of agricultural inputs, resulting in environmental problems such as soil erosion, water pollution and greenhouse gas emissions. This finding appears to be consistent with the findings of Raihan et al. (2023). The LNGDP variable is found to have a positive and statistically significant effect on CF at low, medium and high-level quantiles (0.20–0.30–0.40–0.50–0.60–0.70–0.80–0.90). Accordingly, an increase in per capita GDP is associated with an increase in environmental pollution. At the same time, increased GDP per capita and enlarged arable land will increase the CF. Increasing the standard of living for the people requires higher food demand and more arable lands, leading to environmental degradation. The positive effect of the increase in GDP per capita on the CF can be explained by the fact that as income levels rise, people's consumption habits change and they start consuming more animal products. As the production of animal products requires more land, water and energy than plant-based products,

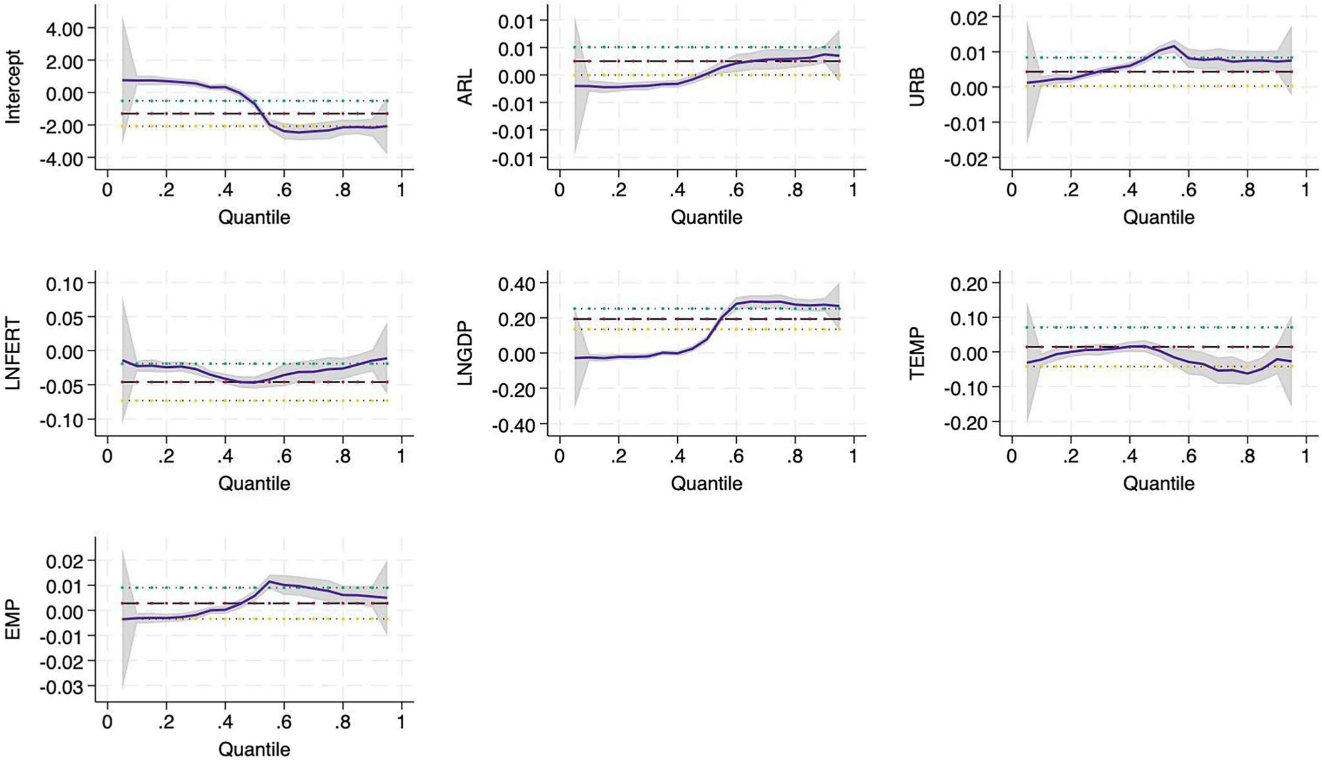

FIGURE 2 | MMQR graphical representation.

this increases the CF. In addition, increased consumption, coupled with rising incomes, can further intensify environmental pressures by increasing overall resource use and waste generation. Urbanisation, annual average temperature and employment do not display a statistically significant impact on CF in any quantile.

In Figure 2, the explanatory variables influencing CF at all quantile levels are represented. The horizontal axis shows the quantiles of the dependent variable, and the vertical axis shows the coefficient magnitudes. The area between the green and yellow lines represents the confidence interval, and the horizontal line in the confidence interval shows the OLS coefficient, which does not change by quantiles. The regression coefficients for quantiles are depicted as lines that fluctuate across different quantiles, accompanied by confidence intervals surrounding them. Thus, conclusions similar to those drawn from Table 8 can be inferred from Figure 2.

5 | Discussion of Results

In recent years, the causes of global environmental issues have been predominantly attributed to production and consumption habits, along with flawed policies in trade processes. Within this context, addressing environmental problems and promoting environmental awareness necessitates primarily focusing on policies developed for producers and consumers. Failure to do so could escalate environmental issues into disasters, including global warming, climate crises and food shortages. Developing new and comprehensive research and increased international collaborations are imperative for formulating effective global policies to tackle these environmental challenges. Soil and agricultural lands are at the forefront of the fight against global environmental and climate problems. Agricultural lands, which are the storehouse of essential nutrients in nature, constitute an important ecosystem that forms a vital space between air, water and living beings. Soil and agricultural lands, the world's most important terrestrial carbon sources, also contribute significantly to the ecosystem cycle by decomposing elements such as microorganisms, nitrogen and sulphur.

This study deals with environmental problems through the lens of the CF. Given data limitations, the first 10 countries with the highest agricultural production (China, India, Indonesia, Brazil, the United States, Nigeria, Turkey, Japan, Argentina and Thailand) have been selected as illustrative examples. As highlighted in the introduction section, which outlines the theoretical and conceptual framework of the study, agricultural production plays a pivotal role in the world's carbon cycle. Consequently, strategies devised for agricultural production, agricultural land and their determinants effectively regulate carbon emissions and achieve carbon neutrality.

The selected sample in the analysis represents the top 10 countries significantly influencing global agricultural production. Furthermore, when considering the chosen determinants of the CF in the analysis, namely GDP, urban population, employment in agriculture, arable land, fertiliser consumption and annual mean temperature, these variables collectively constitute the most substantial group of countries in global production. The selected sample of countries constitutes the largest group in the world's socio-economic structure. Countries like China, India, Brazil and Japan are predominantly seen as essential actors in the global balance, given their economic size, their weight in world trade and their impact on the production–consumption balance. In this context, the study is deemed meaningful for contributing to the literature by analysing the determinants of the CF within the selected sample.

In the analysis, the cross-sectional dependence of the variables was examined. According to the results of the Pesaran (2004) CD_{lm} test, it was concluded that there is cross-sectional dependence among the variables. Then, the (PANIC) unit root test, developed by Bai and Ng (2004, 2010) from second-generation stationarity analyses, was employed. It revealed that the variables are not stationary at levels but become stationary at the I(I) level when first-order differences are considered. This suggests that policy shocks aimed at the CF in the top 10 countries with the most intensive agricultural production could contribute to reducing environmental pollution in the medium and long term. In other words, measures taken regarding the CF within the scope of policies targeting factors such as urban population density, employment in the agricultural sector, fertiliser usage in agricultural production and arable land in these countries could yield greater economic and social returns than focusing solely on agricultural products.

According to the Delta test results developed by Pesaran and Yamagata (2008), the slope coefficients among units change in the long term, indicating that the slope coefficients of the included variables are heterogeneous. This reveals that the effect of a possible change in the variables LNGDP, URB, EMP, ARL, LNFERT and TEMP on CF varies from country to country. Finally, the Durbin–Hausman co-integration test developed by Westerlund (2008) was conducted in the study to examine the presence of a long-term relationship among the variables. The results indicated the existence of a long-term co-integration relationship among the included variables. Following the confirmation of co-integration, the co-integration coefficients and their significance were tested and interpreted. Due to the non-normal distribution of the variables, quantile regression analysis was used to estimate the coefficients of the independent variables. According to the MMQR estimation results, the ARL variable was found to have a positive and statistically significant effect on CF at medium and high-level quantiles. The LNFERT variable was found to have a negative and statistically significant impact on CF at low, medium and high-level quantiles. The LNGDP variable was found to have a positive and statistically significant effect on CF at low, medium and high-level quantiles.

The positive and statistically significant effect of arable land on CF, particularly at medium and high quantiles, indicates that increases in agricultural land use may exacerbate environmental pressures more severely in countries already experiencing high cropland demands. This nonlinear relationship suggests that the environmental burden of land expansion becomes more intense as cropland use increases, pointing to diminishing environmental returns to scale. Therefore, rather than expanding arable land, countries should prioritise enhancing productivity and efficiency of existing agricultural land through sustainable practices. This insight is crucial for designing targeted policies that aim to balance food security needs with ecological preservation.

Direct comparisons cannot be made between the study's findings and the literature due to the inadequacy of existing studies. Research on the determinants of the CF, identified as an environmental indicator, is quite limited. Within this scope, the literature primarily consists of theoretical and technical research focused on the agricultural sector. Thus, the study on the CF and its determinants is believed to make a novel contribution to the literature. Besides, the chosen model, methodology, sample and variables used in the analysis demonstrate the uniqueness of the study. However, upon comparison with existing literature, the study yields the following interpretations. The findings of this paper are consistent with those presented by Ben Jebli and Ben Youssef (2019), Rehman et al. (2020), Bas et al. (2021), Koondhar, Tan, et al. (2021), Koondhar, Udemba, et al. (2021), Si et al. (2021), Kara et al. (2022), Baig et al. (2023), Rehman, Alam, et al. (2022), Magazzino et al. (2023) and Raihan et al. (2023). Conversely, our results contradict the findings of Niu et al. (2020), Kara et al. (2022), Rehman, Ma, et al. (2022), Guo et al. (2022), Magazzino and Santeramo (2023) and Ma et al. (2024). Such contradictions may be attributed to differences in the chosen model, methodology, variables and sample size.

The findings of this study are particularly relevant for emerging and developing economies, many of which face similar challenges related to rapid urbanisation, population growth and increasing agricultural demand. Policies that promote efficient fertiliser use and limit unnecessary cropland expansion, as observed in the top agricultural countries, can be adapted by developing economies to achieve more sustainable agricultural practices. Furthermore, recognising the asymmetric effects of GDP growth on land use pressure can help these countries design tailored strategies that balance economic development with environmental preservation.

The significant positive effect of GDP per capita on CF across nearly all quantiles suggests that rising incomes in leading agricultural countries contribute to increased land demand, both for food consumption and bioeconomic production. For example, in countries such as China and Brazil, higher income levels are often associated with shifts in diet patterns towards more land-intensive animal products. Likewise, the negative relationship between fertiliser use and CF in countries like India or Indonesia could reflect the effectiveness of input-intensive agriculture in enhancing land productivity, thus reducing the need for further cropland expansion. These patterns reinforce the notion that country-specific agricultural policies and consumption dynamics play a critical role in shaping environmental outcomes.

6 | Conclusions and Policy Recommendations

The findings of this study offer valuable insights for policymakers aiming to balance agricultural expansion with environmental sustainability. First, the significant positive effect of GDP per capita on CF implies that economic development tends to intensify environmental pressure through increased land demand for food and bio-based consumption. Therefore, economic growth strategies must be accompanied by sustainable land use planning. Second, the negative relationship between fertiliser use and CF suggests that policies encouraging efficient fertiliser application can enhance agricultural productivity and reduce pressure on land. This calls for targeted agricultural extension services and subsidies to promote responsible input use. Third, the positive impact of arable land on CF in high-impact countries indicates the need for regulating land conversion and investing in soil quality improvement rather than expanding land. These insights can guide tailored, country-specific strategies to meet SDG 2 (Zero Hunger) and SDG 15 (Life on Land) simultaneously, especially in rapidly developing agricultural economies.

In this study, we have investigated the determinants of CF in the top 10 agricultural countries from 1991 to 2021. We have considered the determinants of GDP per capita, urbanisation rate, employment in agriculture, arable land, fertiliser consumption and annual mean temperature among the determinants. We have checked cross-sectional dependence among the variables of the panel, and we have found that CSD exists for this panel. We applied the unit root test, and all variables (except annual average temperature) were integrated I(1). The slope homogeneity test has shown the heterogeneity of the variables of the investigated panel, and the Durbin–Hausman co-integration test has shown there is a long-term relationship among the variables. To study the asymmetric impact of the determinants on CF, we have applied MMQR, and we have found that arable land has a significant and positive impact on CF in medium and high quantiles. Fertiliser consumption and GDP per capita present a significant negative and positive impact, respectively, on CF in almost all quantiles, while urbanisation, annual average temperature and employment in agriculture do not present a significant impact on CF. Summarising results, economic growth and expansion of arable land are detrimental for the environment, though they are good for increasing food production. To fight against this negative environmental effect, fertilisers are important to increase land productivity. This way, balance can be reached between meeting global food demands and protecting the environment at the same time.

For economic literature, this study has important implications. It is the first study dealing with CF and its socio-economic and environmental determinants. Previous studies have focused on the relation between agricultural factors and carbon or GHG emissions, and most of the works were elaborated for China. CF is a more comprehensive ratio expressing the environmental impact of agriculture compared to gas emissions. Other studies have focused on arable land as the dependent variable. Determinants that were included in the analysis belong not only to the agricultural sector, but they also express the socio-economic development level. Thus, this estimation model includes a comprehensive dependent variable, namely CF, and a wide range of factors covering the agricultural sector and socio-economic development area. The analysis is conducted for an overall panel of the top 10 agricultural countries, but also on each country included in the analysis. That can bring important insights in terms of policy and practical recommendations for these countries where the agricultural sector is much extended and agricultural production is oriented toward fulfilling both internal demand and export demand.

This study provides a novel contribution to the existing literature by being the first to employ a Method of Moments Quantile Regression (MMQR) to investigate the socio-economic and climatic determinants of CF. Unlike previous works that primarily focused on CO_2 or greenhouse gas emissions, our study leverages CF as a more integrative and comprehensive environmental indicator. Furthermore, by examining the distributional effects across quantiles, the analysis reveals heterogeneous impacts that would be masked in mean-based approaches. This methodological innovation and the wide scope of determinants allow for more nuanced and effective policy recommendations tailored to varying levels of land use pressure.

Based on the results, we can state that using fertilisers can help diminish the CF by increasing the fertility and productivity of the cultivated areas. At the same time, increased GDP per capita and enlarged arable land will increase the CF. Increasing the standard of living for the people requires higher food demand and more arable land for that purpose. Thus, the impact on land use as a natural resource is negative. Since robust economic growth needs to continue, adopted measures should target restoring forests, changing cropland from time to time to allow land to regenerate its productive capacity, using previously abandoned land, using fertilisers to increase land productivity and fertility, investing in technological innovations for agriculture, or changing dietary habits and reducing food waste. For the most effective measures, adopted measures should aim at both the supply and demand sides of this problem of increasing CF. To implement necessary measures on the demand side, the public authorities should initiate a large information campaign to increase population knowledge on this serious issue affecting the entire planet and the future of future generations. Land is indissoluble and related to our living, our feeding and our entire socio-economic activity. In this respect, it must be preserved and most efficiently used, so this vital resource should regenerate its productive capacity.

Our results show that only fertilisers can support diminishing the negative impact of cropland on the environment in all quantiles for the entire panel, while GDP growth and arable land display a strong negative impact on the environment for the whole panel. Urbanisation also displays a weak and positive impact on CF, while annual average temperature and employment are not significant at the panel level. For Brazil and Indonesia, this expansion can deteriorate the environment. In India, the average annual temperature is associated with a CF, while in Indonesia, arable land can be associated with a CF because of large arable land surfaces there. In India, Indonesia and Argentina, employment levels can be associated with CF because of high employment numbers in agriculture there as per the datasets we have used in the analysis. Looking at the results for the whole panel but also for each of the investigated countries, public authorities can design specific policies in the agriculture sector. Fertilisers can alleviate the negative impact of continuous urbanisation and economic growth or expansion of arable lands on the environment by increasing land productivity for all countries, especially in countries such as Brazil and Indonesia with a large share of arable lands according to the datasets. So, there are extensive agricultural practices applied in those countries and things can change only through technological innovations in this specific sector.

In this context of rapid urbanisation and urbanisation agglomerations, rapid and robust economic growth rates, and a growing population, and because of increasing average global temperature, all countries must struggle to adopt proper policy measures for the agricultural sector, for more efficient use of arable land, for relocating cropland to increase land productivity, for irrigation infrastructure and for using fertilisers for the crop. All these will require large financial support granted to farmers for these objectives so that the effect on the ecosystem should be much diminished. The agricultural sector is facing most of the pressures related to economic development, climate change and natural disasters caused by climate change. Thus, farmers need public support in terms of financial funds and subsidies or fiscal facilities to make agriculture more efficient and diminish the negative effects of expanding necessary cropland. This public support must be complementary to private investments in this sector. Public-private partnerships can be the best practical solution for reaching all the goals mentioned above by allocating large financial funds for research and development in this area, obtaining technological innovations necessary for agriculture, and diminishing the opportunity cost of expanding cropland.

The contribution of this paper is reflected at both theoretical and practical levels. It is the first study dealing with the determinants of CF, and it performs an overall quantile panel analysis for the top 10 agricultural countries, as well as a distinct analysis for each of the countries included in the analysed panel. So that, emphasising socio-economic and agricultural determinants that are most effective for each country and their impact, public authorities can design the most effective and appropriate measures that can support cropland extension without harming the environment, thus achieving the SDGs associated with food security and climate change.

Directions for further research should focus on investigating more determinants of CF, such as land productivity or land rent, total population, technological innovations, food waste, external trade, or natural resource extraction such as coal and oil for economic purposes. Also, the analysis can be performed for regions or countries from Africa, Latin America and South Africa where cropland expansion is the highest, with a significant negative impact on biodiversity loss and the ecosystem as a whole. These specific regions face significant food security problems. Alternative estimation methods and tests can be applied for further analysis.

The main limitations of the research can be summarised as follows: (1) The selection of the country sample as the top 10 countries with the highest agricultural production (China, India, Indonesia, Brazil, the United States, Nigeria, Turkey, Japan, Argentina and Thailand). (2) The use of annual data from 1991 to 2021 for the variables included in the model due to moderate data constraints. (3) Based on data constraints, GDP, urban population, employment in agriculture, arable land, fertiliser consumption and annual mean temperature are selected as determinants of the CF.

Author Contributions

Ibrahim Cutcu: conceptualization, data curation, formal analysis, and writing initial draft. **Magdalena Radulescu:** conceptualization, validation, investigation, methodology, software, reviewing and editing.

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Conflicts of Interest

Magdalena Radulescu is an Associate Editor for GJ and a co-author on this article. M.R. was blinded to the peer review process; management of the peer review process and decision-making for this article were undertaken by the Editor-in-Chief.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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