RESR Revista de Economia e Sociologia Rural

ISSN 1806-9479

ARTICLE

Carbon pricing in agriculture: a systematic literature review

Precificação do carbono na agricultura: uma revisão sistemática da literatura

Daniela Tatiane de Souza[1]*, Fernando Antônio de Pádua Paim[1], Lauro Rodrigues Nogueira Júnior[1], Carlos Cesar Ronquim[1], Pedro Gilberto Cavalcante Filho[2]

[1]Empresa Brasileira de Pesquisa Agropecuária (Embrapa Territorial), Campinas (SP), Brasil. E-mails: daniela.souza@embrapa.br; fernando.paim@embrapa.br; lauro.nogueira@embrapa.br; carlos.ronquim@embrapa.br

[2]Universidade Estadual de Campinas (UNICAMP), Campinas (SP), Brasil. E-mail: pedro.gilberto@hotmail.com

How to cite: Souza, D. T., Paim, F. A. P., Nogueira Júnior, L. R., Ronquim, C. C., & Cavalcante Filho, P. G. (2025). Carbon pricing in agriculture: a systematic literature review. Revista de Economia e Sociologia Rural, 63, e288293. https://doi.org/10.1590/1806-9479.2025.288293

Abstract: Carbon pricing involves assigning a monetary value to greenhouse gas emissions. This paper systematically reviews the state of carbon pricing in global agriculture over a 20-year period. Based on a systematic literature review, carbon valuation methods were correlated with prices attributed to determinants identified in academic publications, as well as extrapolated to the Brazilian agricultural environment. There was variation in carbon prices (minimum of USD 2.6/tCO2e and maximum of USD 157.5/tCO2e), determined by different socio-economic, agricultural and geographical heterogeneities. Our results showed negative relationship between Gross Domestic Product (GDP) per capita and CO2 emissions per capita, indicating high elasticity of emissions in response to changes in carbon prices. There was also positive relationship between nitrogen fertilizer use per capita and carbon price. In 2021, the estimated carbon value for Brazilian agriculture using quantile regression was USD 11.54/tCO2e. It is therefore critical that scientifically robust carbon pricing methodologies be applied to agriculture to serve as benchmarks for national environmental valuation systems.

Keywords: agriculture, carbon pricing, CO_2 emissions.

Resumo: A precificação do carbono envolve a atribuição de um valor monetário às emissões de gases de efeito estufa. Este artigo realizou uma revisão sistemática sobre preços do carbono na agricultura mundial nos últimos 20 anos. Partindo de uma revisão sistemática da literatura, os métodos de valoração e os preços atribuídos ao carbono foram correlacionados a um conjunto de determinantes identificados em publicações acadêmicas e extrapolados para o contexto da agricultura brasileira. Constatou-se variação nos preços do carbono (mínimo de USD 2,6/tCO_2e e máximo de USD 157,5/tCO_2e) com diferentes variáveis socioeconômicas, agrícolas e ambientais determinando o preço do carbono. Os resultados revelaram correlação negativa entre o Produto Interno Bruto (PIB) per capita e as emissões de CO_2 per capita, indicando elevada elasticidade das emissões em resposta às mudanças na precificação do carbono. Além disso, observou-se associação positiva entre o uso de fertilizantes nitrogenados per capita e o preço do carbono. Em 2021, o valor do carbono estimado para a agricultura brasileira com o uso de uma regressão quantílica foi de USD 11,54/tCO_2e. Ressalta-se a importância do uso de metodologias cientificamente robustas para a precificação do carbono na agricultura, a fim de servir como referência para os sistemas nacionais de valoração ambiental.

Palavras-chave: agricultura, precificação do carbono, emissões de CO_2.

1. Introduction

Carbon pricing mechanisms and frameworks such as marginal abatement cost (MAC), shadow price and social cost can provide key parameters for setting greenhouse gas emission reduction targets. Institutions can transition to a low-carbon economy by internalizing carbon values. Carbon value estimates can also be embedded in economic models and internal corporate pricing frameworks to guide the design of abatement proposals (Hafstead et al., 2021; Ranson, 2020).

In 2021, agricultural activities contributed to 16.2 billion metric tons of CO_2e emissions globally, a 10% rise since 2000. Carbon dioxide made up 50%; methane, 32%; nitrous oxide, 14%; and fluorinated gases, 3% (Food and Agriculture Organization of the United Nations, 2023). Livestock, particularly through manure management and enteric fermentation, was responsible for nearly 80% of these emissions. Rice cultivation also significantly contributed to methane emissions. Some agricultural practices, such as improved livestock management and fertilizer adjustments, can sequester carbon and reduce emissions (Tang et al., 2016b; Bonesmo et al., 2012). Brazil is a major greenhouse gases (GHG) emitter due to land-use changes and enteric fermentation in livestock (Estevam et al., 2023). The country also leads in pesticide consumption, 0.72 million metric tons, which accounts for 20% of the total global consumption. Reducing chemical use through organic agriculture could reduce emissions while maintaining food security. Brazil's RenovaBio and ABC+ Plan promote sustainable, low-carbon agriculture, in line with the emissions targets of the Paris Agreement (United Nations, 2020).

The research problem addressed in this paper is how commonly mentioned factors influence the value of carbon in the agricultural sector. In order to try and solve the carbon pricing issue in agriculture, this paper attempts to identify valuation methods, carbon prices and their determinants in worldwide agriculture between 2004 and 2024, as well as to model Brazilian agriculture's carbon price. The literature on carbon pricing in Brazil did not seem to put much emphasis on the pricing itself, but rather sought to uncover aspects more related to low-carbon agriculture and aspects related to carbon pricing determinants (Gurgel & Laurenzana, 2016; Gouvello et al., 2010; Carvalho et al., 2022). This article addresses this gap by systematically integrating carbon pricing, and applying the combined results of the systematic review to the Brazilian economy. Furthermore, given the lack of a reference value for the price of carbon in Brazilian agriculture, this study provides a practical basis for the development of specific policies and strategies that will help guide the implementation of low-carbon practices in the agricultural sector.

The review of existing methodologies provided a broad context for the study and helped to understand how carbon prices have been estimated globally. Given the heterogeneity of these methodologies, a quantile regression approach was adopted. The combination of the carbon prices obtained in the systematic review with the modeling of the data has been carried out through meta-analyses such as the one performed by Tol (2024). For the Brazilian case, the work of Campoli & Feijó (2022) stands out. This is an accepted procedure, especially in the fields of health, economics and environmental sciences. Once the problem of data heterogeneity is overcome, the procedure makes it possible to apply the results to different contexts and predict how the phenomenon may behave in new situations (Malange, 2015).

Carbon valuation systems involve governmental and institutional elements that interact through valuation methods, carbon prices, regulatory policies, and country-specific dynamics. The EU Emissions Trading System (EU ETS), for example, caps emissions, affects carbon prices, and encourages low-carbon investments (Grosjean, 2017). Factors such as income levels, CO_2 emissions, and the economic role of agriculture can affect carbon prices. Institutions such as the IPCC and World Bank initiatives such as the Carbon Pricing Leadership Coalition (CPLC) are critical in shaping carbon policies and markets.

2. Theoretical Foundation

Voluntary or regulated carbon markets have different advantages for each type of carbon pricing system. Marginal Abatement Cost (MAC) curves, integrated methodologies and optimization and programming models are some relevant examples in this context (Wang, 2015). In the case of voluntary pricing markets for carbon emissions, it may be an option for companies to include them as environmental commitments or corporate social responsibility obligations. In regulated pricing markets, government policies play a central role in setting carbon prices with the aim of achieving emission reduction targets. The use of integrated methods and shadow pricing allows for an understanding of the impacts of climate change and environmental externalities (Tang, 2016; Wang et al., 2022).

2.1 Carbon pricing models

Integrated assessment models (IAMs) are often used to calculate social cost of carbon, which takes into consideration a variety of factors, such as greenhouse gas emissions, climate impacts, adaptation costs, impacts on agricultural production, human health, and others (Nordhaus, 2017). The social cost of agricultural carbon in IAMs could be obtained by decomposing its contribution to total greenhouse gas emissions. According to the study conducted by Anthoff et al. (2011) on 16 global regions using the FUND model for the Climate Framework for Uncertainty, Negotiation and Distribution, the distribution of the social cost of carbon across sectors is a function of the rate of time preference. The magnitudes of cooling and agriculture are almost similar, with respect to integrated models for general equilibrium or partial equilibrium problem formulations. Their magnitudes are -6.5/tCO_2e and 6.8/tCO_2e at a 3% discount rate, respectively. But environmental IAMs are the most common instrument that could be found for assessing economic policies with respect to the environment (Anthoff et al., 2011).

Studies on carbon pricing in Brazil are limited to agriculture. The economic impact of adopting mitigation technologies was analyzed by Gurgel & Laurenzana (2016) in a computable general equilibrium framework for the time horizon 2015 to 2030. The adoption of one of the no-till practices would contribute the most to reducing CO_2e emissions to 16 Mt in the cropland category if carbon were priced at USD 0.25/tCO_2e. On their turn, emissions from the livestock category would be reduced by 104 MtCO_2e at a carbon price of USD 7.85/tCO_2e. For agriculture, the average mitigation cost was US$ 5.41/tCO2e (average for agriculture in 2017 converted to 2021 prices). Another computable general equilibrium study was that of Carvalho et al. (2022), which, although it did not single out a specific value for agriculture, showed that the introduction of carbon prices between R$ 10 and R$ 2,000 (USD 1.85 and USD 371 at 2021 prices) would produce greater reduction in emission volumes in livestock production.

The approach to carbon pricing based on the MAC curve illustrates the marginal cost of an additional unit of pollution reduction relative to total pollution in a country/sector. McKinsey & Company (2009) estimated abatement costs in Brazil's agricultural sector, and are leading in-depth research on abatement costs for different types of GHG mitigation technologies. They have identified GHG reduction opportunities in a number of sectors in Brazil in 2030, with implications for technologies and practices that could be adopted globally to reduce emissions. One of the largest sources of GHG emissions in the agricultural sector is livestock production, mainly as a result of residues on pastures and enteric fermentation by the animals. The amount of marginal costs related to various projects implemented in agrarian activities was quite insignificant and estimated at the level of approximately € 2 per ton of CO_2 in 2007 (USD 5.37 at 2017 prices adjusted to 2021 values) as estimated by McKinsey & Company (2009).

Other methods include pricing using the shadow price while setting parameters for optimization/linear programming analyses. In particular, the shadow price of CO_2 refers to the forgone benefits received from reducing one extra unit of CO_2 emission under given technology constraints. The productive micro-efficiency model usually looks at the overall reduction potentials of CO_2

emissions balancing out technological aspects and complex economics. It examines a variety of production aspects while trying to understand changes in terms of producing fewer CO_2 particles than before, therefore allowing the measurement of the associated opportunity cost. In 2016, Yamamoto et al. (2022) conducted a study on carbon tax policies and their impact on the agribusinesses in Vietnam using a multi-product system including rice, livestock and aquaculture. Farmers operating within the Mekong Delta area recorded lower technological efficiency levels compared to those found elsewhere, yet they had a lower shadow price for GHG emissions. The author estimated an average shadow price of USD 14.5/tCO_2e for Vietnamese agriculture using a production directional distance function. In the Belt and Road Initiative countries, there were significant variations in carbon shadow prices' dynamics in agriculture, as observed by Wang et al. (2022). During the period of 2000 to 2019, most countries experienced a decrease while only few countries had an increase in carbon price. This general decrease indicates technological progress in carbon abatement within BRI countries. In this line, Mongolia, Vietnam, India, Yemen, Nepal, The Philippines, Indonesia, and Myanmar had high average annual growth rates in their agricultural carbon shadow prices, revealing escalating difficulties in mitigating agricultural carbon emissions, especially considering their relatively low level of economic development. Conversely, the remaining 32 countries experienced different degrees of decreases in terms of agricultural carbon shadow prices. In China and Russia and Kyrgyzstan together with Lebanon significant annual average declines, ranging from 29.9%, 18.45%, 17.43% to 17.09% respectively, were noticed. Additionally, central eastern European nations such as Croatia, Georgia, Greece and Estonia experienced significantly lower annual average declines ranging from 12.32% to 14.65%. Other similar studies include those of Wang et al. (2022), Guan et al. (2018) for China, and by Tang et al. (2016b) for Australia.

Biophysical processes include agricultural simulation models that focus on optimization and linear programming. In general, a combination of biological and economic data is used along with environmental information to study the impact of different agricultural practices on climate change and agricultural performance. In particular, the study by Gouvello et al. (2010) investigated the transition from a high to low carbon economy in Brazil, focusing more on the agricultural sector. In this regard, the simulation was carried out using a georeferenced model that evaluated different mitigation and carbon sequestration options proposed within the particular scenario considered. The study identified a potential reduction of 302 million tons of CO_2e by 2030 at USD 6/tCO_2e (2017 prices, adjusted to 2021 values) on MAC curves for technologies used in different sectors over the period between 2010 and 2030. This reduction resulted from the combined adoption of practices to reduce deforestation and intensify livestock production. Thus, these results suggest that the adoption of these measures would be an effective GHG mitigation strategy for the agricultural sector.

2.2 Determinants of carbon pricing in agriculture

Pricing models generally take into account various factors that affect the value of carbon, which may be used as a reference for climate change mitigation policies. In agriculture, these determinants may vary by region, crop type, and the specific characteristics of each agricultural system. In the current literature, GHG emissions are one of the principal factors influencing carbon valuation. Tang & Wang (2023) showed negative relationship between taxing emissions and the level of CO_2e emissions in China in 2022. With an emission tax rate of ¥50/tCO_2e (USD 7.05/tCO_2e), emissions were reduced by 8% compared to the baseline scenario. Doubling this rate would reduce agricultural emissions by 17% relative to the baseline. Raihan et al. (2023) showed that a 1% increase in agricultural value added is associated with a reduction in CO_2

emissions of 1.37% in the long term and 0.65% in the short term. However, GDP and energy consumption were found to have a positive and statistically significant impact on CO_2 emissions. The study identified an inverted U-shaped relationship between economic growth and pollution, as evidenced by the positive coefficient of GDP and the negative coefficient of GDP squared, thus supporting the validity of the Environmental Kuznets Curve (EKC) hypothesis.

In the context of agricultural inputs affecting carbon prices, Baccour et al. (2021) conducted an evaluation of measures to improve nitrogen efficiency and reduce nitrogen loads to air and water. The authors focused on the effectiveness of the N optimization measure, which resulted in a significant abatement of about 0.3 $MtCO_2e$ at negative cost in 2014. In addition, the N optimization measure provides benefits to farmers by reducing their private costs and substituting manure fertilization by synthetic fertilization. Studies addressing the shadow price place great emphasis on production factors (capital, labor, and land) as determinants of carbon value (Burke et al., 2019; Guan et al., 2018; Yamamoto et al., 2022). However, Wang et al. (2014) comment that countries experiencing an increase in the shadow price of agricultural carbon are drawing lessons from advanced emission reduction technologies and practices, gradually reducing their reliance on material factors of production while increasing the contribution of nonmaterial factors of production to agricultural progress. A notable example is China's proactive adoption of environmental technologies. China attaches great importance to technical cooperation with Israel in desertification control and water-efficient irrigated agriculture.

On the other hand, in the realm of carbon market equilibrium, the price of carbon credits is strongly influenced by the emissions reduction target set. According to Bakam et al. (2012), the price of carbon remains low because farmers contributing carbon credits to the market have achieved emission reductions at a relatively low cost by using their cheapest abatement options. However, as reduction targets increase, the price of carbon rises sharply and more and more farmers become buyers of carbon credits, as farmers are forced to resort to more expensive abatement measures to meet these targets. Conversely, when reduction targets are set at lower levels, the supply of carbon credits exceeds demand. This is because most farmers can meet their obligations using available technology, resulting in a surplus of carbon credits on the market.

3. Methodology

The systematic review included publications that addressed carbon pricing methodologies in agriculture, limited to emissions from crops and livestock, with inclusion and exclusion criteria based on the PRISMA methodology (2020). The research methodology was developed in two steps. First, a comprehensive review of the literature on carbon pricing in agriculture was conducted. The second step was to assess how these prices are determined, followed by modeling carbon price for Brazilian agriculture. Methodological procedures similar to those proposed in this study were also employed in the research conducted by Wang et al. (2019) and Kumara et al. (2023).

3.1 Step 1 - Systematic Literature Review

The research included publications from January 2004 to January 2024, the last 20 years. The databases used were Science Direct, Web of Science, Springer, Wiley Online and Google Scholar. The keywords used in the database search covered the different methodologies used to assess carbon in agriculture. In the indexed journals, the search made use of Boolean search engines: TITLE-ABS-KEY ("carbon pricing" AND "agriculture" OR "abatement costs" AND "agriculture" OR "shadow price" AND "agriculture" OR "integrated assessment models" AND "agriculture") AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (SRCTYPE, "j")). In

Google Scholar, the query was made using the advanced query tool with Boolean operators in Portuguese and English: carbon pricing in agriculture (precificação do carbono na agricultura); integrated assessment models in agriculture (modelos de avaliação integrados na agricultura); marginal abatement cost (MAC) in agriculture (custo marginal de abatimento na agricultura); social cost of carbon (SCC) in agriculture (custo social do carbono na agricultura); shadow price of carbon in agriculture (preço sombra do carbono na agricultura).

The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses – PRISMA – (Page et al., 2021). Table 1 summarizes the inclusion and exclusion criteria of the systematic review and the quantification of the search results. The initial search yielded 89 publications (Figure 1). A spreadsheet was developed to organize the data and ensure that all publications met the specified criteria, incorporating details such as source, publication type, title, year, authors, country, analysis period, sector/activity, segment, study level, methodology, variables analyzed, average agricultural carbon price, and abstract notes. After eliminating duplicate files (9 publications), 80 publications remained listed for evaluation. In case of disagreement on any of the criteria, consensus was reached through discussion. The included publications were reviewed and documented several times. Exclusions resulted in 70 publications for analysis. Based on an analysis of the title and abstract of the document, the full text was then assessed for eligibility, leaving 44 publications for an initial descriptive statistical analysis. From this total, 12 publications were excluded because they contained data on carbon prices at a global/regional level, resulting in a set of 32 publications with carbon values broken down by country. In Brazil in particular, only three studies were found that quantified carbon prices in agriculture within the analysis period.

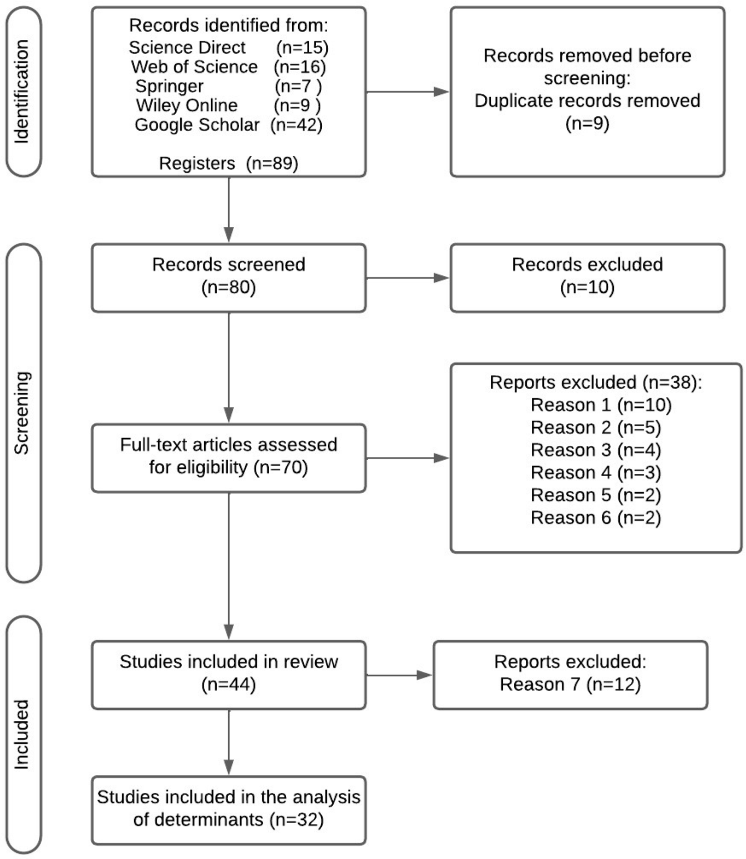

Figure 1. PRISMA 2020 flow diagram. Source: Prepared by the authors based on Page et al. (2021).

Table 1. Reasons for exclusion.

Number	Reason for exclusion	Register
1	Lack of prices for agriculture in general	10
2	Literature review only	5
3	Very specific segment of agriculture, not reporting values for crops and livestock in general	4
4	Inclusion of additional sectors such as forestry	3
5	Pricing in terms of carbon sequestration	2
6	Metric incompatibility	2
7	Data not disaggregated by country, only in global/regional terms	12

Source: Prepared by the authors

In order to standardize the values for the same year, the carbon prices were converted to base year values and then adjusted for the year 2021 by a price index based on the annual variation of inflation in each country, according to the International Monetary Fund (2022). The base year used was 2017, as the information for GDP per capita measured in Purchasing Power Parity (PPP) also refers to that year (World Bank, 2022).

3.2 Step 2 - Analysis of carbon price determinants and modeling carbon price for Brazilian agriculture

The combination of carbon prices and variables obtained in the systematic review with the modeling of data specific to the Brazilian context constitutes an extrapolation meta-analysis. This methodological approach has been used in various fields, with a highlight to the work of Tol (2024). It also allows the combined results to be used to predict how the phenomenon may manifest itself in new contexts or situations (Campoli & Feijó, 2022). In this type of analysis, the sensitivity of estimates largely depends on the consistency of the included studies (Malange, 2015). To prevent variation in the context of the studies from affecting the precision of the combined estimates, robustness tests and sensitivity analyses were used to assess how the estimates vary when different studies or subgroups of data are included or excluded from the analysis.

The information obtained from the systematic literature review (step 1) was supplemented with a set of data to identify the determinants of carbon prices in the countries targeted by the studies. Studies employing the MAC curve have theoretically supported the selection of agronomic variables, such as fertilizers, pesticides, and machinery usage. In contrast, studies utilizing integrated models have placed greater emphasis on variables related to GDP, including the contribution of agriculture to GDP and the proportion of agricultural land. In all studies, the variables related to carbon cycle (CO_2 emissions) and territorial expansion (agricultural area) stood out. Table 2 shows the variables, their source and description.

The study organized variables into dependent and explanatory categories to construct a regression model examining their relationships. Explanatory variables for carbon pricing were obtained from the World Bank, FAO, and USDA, while carbon prices were derived from a systematic literature review. Precision in assigning explanatory variables over the relevant periods was crucial. Data were structured in a cross-sectional format, encompassing Australia, Brazil, Canada, China, India, Ireland, Scotland, Spain, the United Kingdom, the United States, and Vietnam.

Table 2. Variables selected for the analysis of determinants.

Variable	Source	Description
Dependent variable		
Carbon price (USD/tCO_2)	Systematic review	Systematic literature review, based on Science Direct, Web of Science, Springer, Wiley Online and Google Scholar.
Explanatory variable		
GDP (PPP) – constant prices 2017 (USD/cap/yr)	World Bank (2022)	GDP is gross domestic product converted to international dollars using constant 2017 purchasing power parity (PPP) rates.
Share of agriculture in GDP (%)	Food and Agriculture Organization of the United Nations (2021)	Agriculture, forestry, and fishing, value added (% of GDP).
Share of employment in agriculture (%)	Food and Agriculture Organization of the United Nations (2021)	Percentage of the total workforce employed in agriculture.
Share of agricultural land (%)	Food and Agriculture Organization of the United Nations (2021)	Share of land area that is arable, under permanent crops, and under permanent pastures.
Emissions of CO_2e in agriculture (kg/cap/yr)	Food and Agriculture Organization of the United Nations (2021)	The FAOSTAT domain emissions totals disseminate information estimates of greenhouse gas (GHG) emissions in CO_2e, measured in kilotons. The latter are computed by using the IPCC's Fifth Assessment Report on global warming potentials, AR5.
Fertilizer use – Nutrient nitrogen N – (kg/cap/yr)	Food and Agriculture Organization of the United Nations (2021)	Data are provided for the three primary plant nutrients: nitrogen (N), phosphorus (expressed as P_2O_5) and potassium (expressed as K_2O).
Pesticide use (kg/cap/yr)	Food and Agriculture Organization of the United Nations (2021)	The pesticides database includes data on the use of major pesticide groups (insecticides, herbicides, fungicides, plant growth regulators and rodenticides).
Livestock manure (kg/cap/yr)	Food and Agriculture Organization of the United Nations (2021)	Amount excreted in manure (N content).
Machinery use per 1,000 ha of agricultural land	United States Department of Agriculture (2019)	Machinery use is measured in units of horsepower. This is divided by total agricultural land to deliver average farm machinery per unit of agricultural land.

Source: Prepared by the authors.

Normalization to a logarithmic scale (excluding percentage-scaled variables) aimed to stabilize variance for robust statistical analysis. Descriptive and exploratory analyses examined data distribution, central tendencies, dispersion, and inter-variable correlations. Given the non-uniform variability of the data, quantile regression was chosen to examine how different quantiles of the dependent variable relate to the independent variables. This allows the relationship between variables to be examined not only at the mean, but also at different quantiles of the distribution of the dependent variable (Alsayed et al., 2020). This is particularly useful in this study, as it allows for the variability of effects to be captured and to understand how factors influence both the low and high values of the different contexts.

The advantages of using quantile regression include greater robustness in the presence of outliers and heteroscedasticity, and less sensitivity to the normality of the errors. The assumptions of quantile regression include the linearity of the relationship between the independent variables and the specific quantile of the dependent variable, the independence of the residuals, and the conditional distribution with respect to the selected quantile. The associated limitations are the sensitivity to extreme outliers and the greater difficulty in interpreting the results of the quantiles (Alsayed et al., 2020). The 0.5 (median) quantile used divided the distribution into two parts, with 50% of the data below and the other 50% above this value. The quantile regression model with carbon prices as the dependent variable and nine explanatory variables is given by Equation 1:

$$CO_2P = \beta_1 + \beta_2 lnGDP + \beta_3 agri + \beta_4 emp + \beta_5 land + \beta_6 lnCO_2 + \beta_7 lnfert + \beta_8 lnpest + \beta_9 lnliv + \beta_{10} lnmach + \varepsilon \tag{1}$$

The dependent variable is carbon price and the explanatory variables are *lnGDP*: natural logarithm of GDP per capita; *Agri*: share of agriculture in GDP; *Emp*: share of employment in agriculture; *Land*: share of land used for agricultural activities; *lnCO$_2$*: natural logarithm of CO_2 emissions per capita; *lnfert*: natural logarithm of fertilizer use per capita; *lnpest*: natural logarithm of pesticide use per capita; *lnliv*: natural logarithm of nitrogen excreted in animal manure per capita; *lnmach*: natural logarithm of machinery use per 1,000 ha of agricultural land; ε : random error with zero mean and variance σ2. After identifying the model with the best fit, the regression coefficients were extrapolated to Brazilian agriculture. As mentioned by Wooldridge (2023), the predicted values of a variable of interest may be estimated based on the data observed for other independent variables. This is done by multiplying the values of the variables for Brazilian agriculture by the corresponding coefficient in the regression model and adding the intercept, if any. It is important to clarify that methods such as the marginal abatement cost curve and general equilibrium models are well-established tools for carbon pricing. Quantile regression, on the other hand, is not a carbon pricing method, but a statistical technique that analyzes different quantiles of the conditional distribution of variables and allows to extrapolate values to the Brazilian reality[1]. The models were tested using the Schwarz (BIC), Akaike (AIC) and Hannan-Quinn (HQC) criteria to assess the quality of the model and to help choose between different fitted models. Lower AIC and BIC values indicate better models, balancing fit and simplicity, with BIC penalizing complexity more. HQC also helps avoid overly complex models, but with a lower penalty than BIC. In addition, the quantile regression was fitted to assess the sensitivity of the model to the presence of heteroscedasticity using the Breusch-Pagan and White tests. The former checks whether the residual variance remains constant with respect to the independent variables, while the latter detects heteroscedasticity without assuming a specific variance form for the residuals.

4. Results and Discussion

4.1 Analysis of data from the systematic literature review

Figure 2 shows the distribution of publications by research source (Figure 2a), country (Figure 2b), year of publication (Figure 2c) and research method (Figure 2d) for the 32 publications evaluated. Regarding the sources of publications (Figure 2a), 7 journal publications came from Science Direct, 6 from Google Scholar, 3 from Web of Science, 3 from Wiley Online and 2 from Springer. All documents (8) and theses (3) came from Google Scholar. The systematic review procedure, based on the evaluation of indexed scientific journals and supplemented by the inclusion of studies identified through Google Scholar, ensured a more comprehensive approach

[1] The dashboard of research data developed by Embrapa Territorial (2024).

to the synthesis of evidence on carbon pricing in agriculture. Regarding the publication origins depicted in Figure 2b, notable contributors include China, Australia, and the United Kingdom, accounting for a substantial portion of publications (31%, 19%, and 16%, respectively). Following closely are Brazil (9%), Ireland, and the United States (6%), along with Canada, India, Spain, and Vietnam (3%). China, being a prominent global agricultural producer, confronts significant environmental hurdles and has directed attention towards carbon pricing as a means to promote sustainable agricultural methods and diminish GHG emissions within the agricultural domain. Similarly, Australia, with its vast expanse of agricultural land, has stood out in this literature. Both countries have implemented an emissions trading system (ETS) and a crediting mechanism, while the United Kingdom has also implemented carbon taxes as compliance instruments. Regarding the period of analysis (2004 to 2024) (Figure 2c), there was a peak of production between 2016 and 2019, corresponding to 50% of the publications studied. The remaining publications were spread over the remaining years, and the search strategy did not identify any publications on the topic between 2004 and 2008. In some research areas, there may be periods when there is a relative dearth of scientific publications due to a variety of factors, such as limited interest from the academic community, or a lack of significant advances in the field. McManus et al. (2023) examined the various factors that influence the citation impact of scientific papers in different countries, such as funding and the progression through authorial decisions, such as collaboration and choice of publication venue (open access, journal quartile, language). The authors hypothesized that many countries may follow different publication trajectories influenced by the resources available to them, resulting in different impact metrics. These factors may affect the availability and quantity of publications found by a search strategy.

Among the identified methodologies (Figure 2d), studies using the MAC curve (34%) and shadow price of carbon (31%) were prominent. Programming and optimization comprised 25% of the studies, while integrated models focused on agriculture and IAMs accounted for 9%. The literature includes a variety of pricing methodologies, such as top-down, bottom-up, or hybrid approaches. Bottom-up approaches emphasize mitigation costs and implementation, while top-down approaches focus on economic feedbacks and welfare costs, and hybrid approaches combine both perspectives (Moran et al., 2011; Eory et al., 2018; Tang et al., 2016a; Vermont & Cara, 2010). The classification of methodologies aimed to create a structured framework, though overlaps were common, especially in studies calculating MAC as the shadow price of emissions constraints. Figure 3 displays a histogram of carbon prices in agriculture, and shows 19 publications with prices below USD 50/tCO_2e, 11 between USD 50/tCO_2e and USD 100/tCO_2e, and 2 above USD 100/tCO_2e. The distribution was not perfectly normal due to varying estimation methods contextualized for each country from 2004 to 2024.

This diversity of data also suggests that there is a great deal of variability in carbon prices, even for a single country. The most emblematic example is China, with a minimum price of USD 2.59/tCO_2e and a maximum price of USD 157.50/tCO_2e, both estimated using the shadow price method, but with other additional values using different methods (MAC, integrated models, optimization/programming). In 2021, China reached an important milestone in its climate policy by launching its national carbon emissions trading market. Despite this achievement, the market currently covers only the energy sector (electricity and heat generation). Price variability in the agricultural sector due to different pricing methodologies creates an opportunity for carbon market regulation, as explored by Zhu et al. (2023) in their study of the Yangtze River Delta region of China. Establishing guidelines that promote comparability between carbon pricing systems in different regions and within the same country may promote a more harmonized approach to dealing with climate change on a global scale.

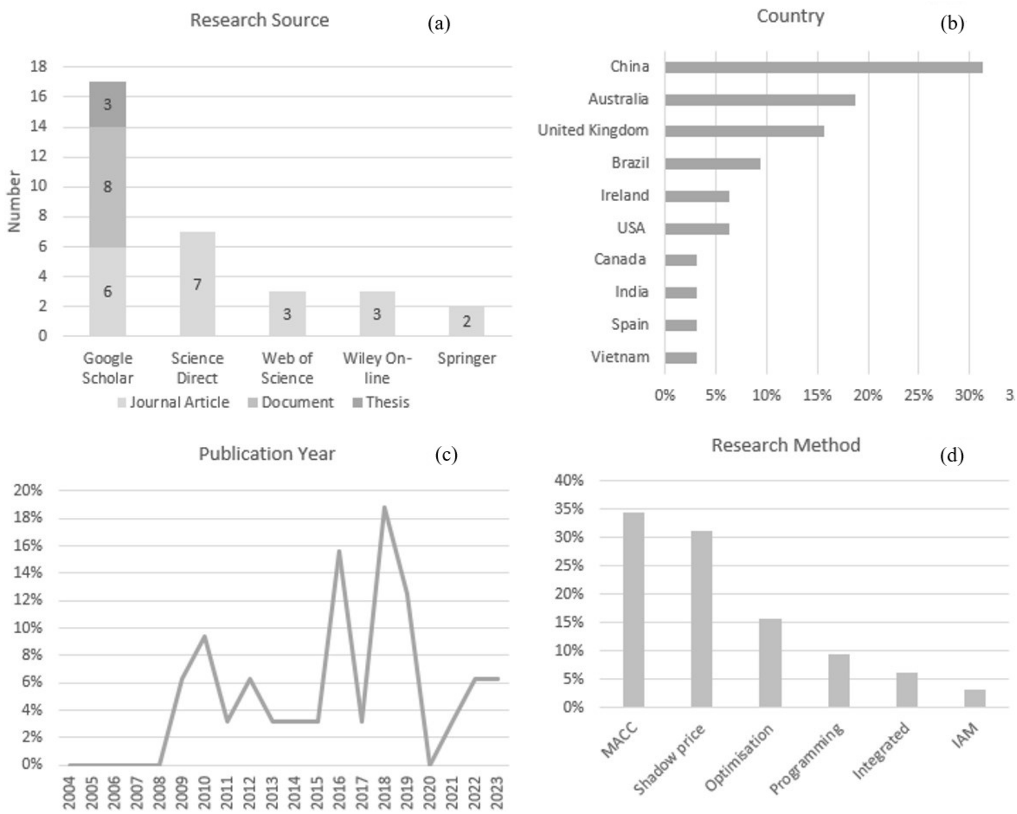

Figure 2. Distribution of publications by research source (a), country (b), year of publication (c) and research method (d) in the 32 publications analyzed. Source: Elaborated by the authors.

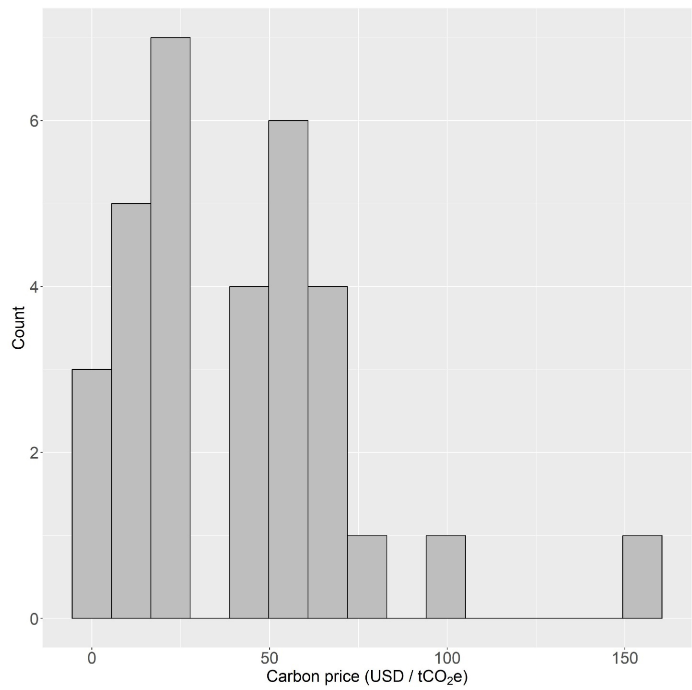

Figure 3. Histogram of carbon price in agriculture. Source: Elaborated by the authors.

4.2 Analysis of the carbon prices determinants

This section provides an assessment of some of the determinants of carbon prices identified through the systematic literature review of the 32 publications analyzed and extracted from institutional statistical sources. Figure 4 illustrates the frequency of occurrence of the variables contemplated by the publications between 2004 and 2024. The variables with the highest frequency were greenhouse gas emissions (21.2%), fertilizers (8.7%), abatement costs (6%), land, machinery and equipment (4.9%), and livestock and gross domestic product (4.4%). This frequency distribution of the variables helped in the selection of the determinants to be analyzed together with the carbon price level. Table 3 shows the descriptive statistics for this set of variables, namely GDP per capita, share of agriculture in GDP, share of employment in agriculture, share of agricultural land, agricultural CO_2e emissions per capita, fertilizer use per capita, pesticide use per capita, livestock manure per capita, machinery use. A first piece of evidence is the difference in standard deviation between the variables. GDP per capita measured in PPP was the variable with the highest standard deviation (USD 22,990/cap/yr), with a minimum value of USD 6,736/cap/yr (India), and a maximum value of USD 93,997/cap/yr (Ireland), reflecting differences in their levels of economic development and income distribution. Another variable showing high standard deviation was the level of agricultural CO_2e emissions (1,69 kgCO_2e/cap/yr), with a minimum of 0.36 kgCO_2e/cap/yr (China) and a maximum of 4,83 kgCO_2e/cap/yr (Ireland). Ireland, with its very small population (5,033,164 inhabitants), ended up with higher per capita emissions than China, which had the largest population in 2021 and the same level of absolute CO_2e emissions from agriculture. The per capita assessment provides a comparison between economies with different population sizes and production structures, and India's per capita agricultural emissions are very similar to those of the Chinese economy. A second piece of evidence points to differences in the dynamics of agriculture at the global level. In the 32 publications reviewed, countries varied significantly in their economic and social dependence on agriculture, as reflected in the share of agriculture in GDP, employment, and land area. While some countries had a relatively high share of agriculture in their economies, others had a more modest presence. Despite lower shares of GDP and employment, some countries retain a high percentage of land area devoted to agriculture, which suggests that the sector remains important in terms of natural resources use and agricultural landscape. This is reflected in the average share of agricultural land, which at 51.95% is higher than the other shares in Table 3.

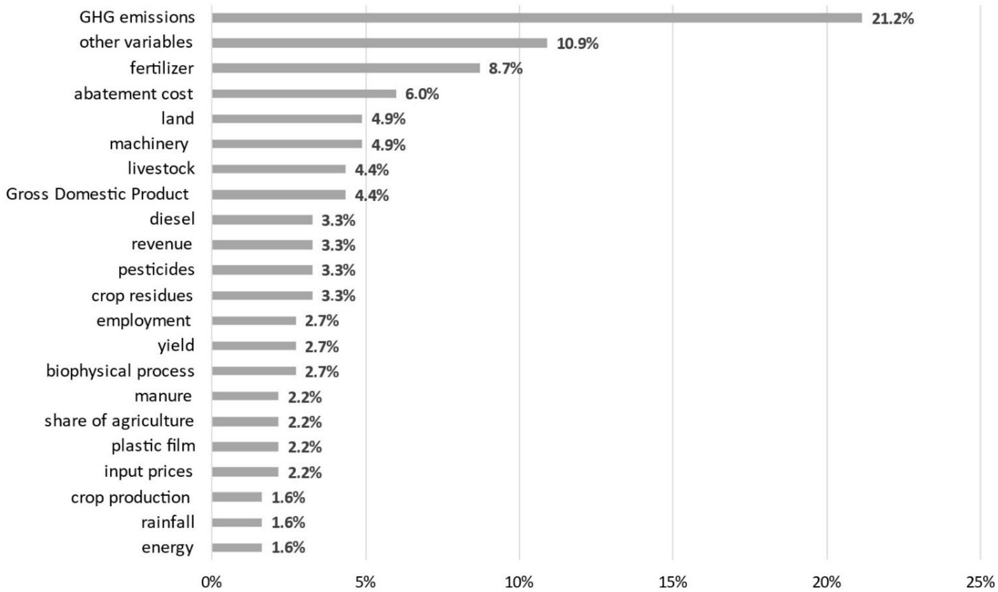

Figure 4. Frequency of variables in publications (%). Source: Elaborated by the authors.

Table 3. Descriptive statistics for carbon price and drivers in 2021.

Variable	Mean	Median	SD	Min	Max
Carbon price (USD/tCO_2e)	41.96	42.83	32.45	2.59	157.50
GDP (PPP) – constant prices 2017 (USD/cap/yr)	39,130	42,260	22,990	6,736	93,977
Share of agriculture in GDP (%)	4.82	2.84	4.17	0.56	16.73
Share of employment in agriculture (%)	12.30	4.42	13.17	1.00	42.86
Share of agricultural land (%)	51.95	55.50	14.64	6.47	72.94
Emissions of CO_2e in agriculture (kg/cap/yr)	1.69	0.69	1.70	0.36	4.83
Fertilizer use (kg/cap/yr)	58.02	39.26	36.67	20.78	140.30
Pesticide use (kg/cap/yr)	0.92	0.39	0.84	0.04	2.52
Livestock manure (kg/cap/yr)	48.25	19.67	53.82	7.05	149.80
Machinery use per 1,000 ha of agricultural land	3.16	1.68	3.12	0.22	7.90

Source: Carbon price was obtained from systematic literature review. Other variables were obtained from World Bank (2022), Food and Agriculture Organization of the United Nations (2021), United States Department of Agriculture (2019), International Monetary Fund (2022).

There was also variation in the adoption of agricultural practices. The use of livestock manure and fertilizer showed standard deviation of 53.82 kg/cap/yr and 36.67 kg/cap/yr, respectively. This variation may be influenced by differences in farming systems, as some economies use more livestock manure as an organic fertilizer, while others rely more on chemical fertilizers. Certainly, this issue highlights the importance of tailored and context-specific approaches to promote agricultural sustainability and mitigate environmental impacts. Figure 5 shows an exploratory analysis of the relationship between carbon prices, GDP per capita, and CO_2e emissions per capita between 2004 and 2021. The same country appears more than once, because there is more than one publication for the same country. Regarding the price of carbon and the level of CO_2e emissions per capita in agriculture, Figure 5a is divided into four quadrants, intersected by an average on the vertical axis (value of USD 41.96/tCO_2e) and on the horizontal axis (emissions of 1,70 kgCO_2e/cap/yr). The same country appears more than once, because there is more than one publication for the same country. The first quadrant contains articles whose countries have carbon prices and emissions below the average for the set of publications, including publications about China and Vietnam. The second quadrant contains publications about countries that have below-average carbon prices but above-average CO_2e emissions per capita, including Australia, Brazil, and Ireland. The third quadrant contains publications with above-average carbon prices and low emissions, again including China, but also India, Scotland, the UK, the US and Canada. Finally, the last quadrant featuring high carbon prices and high emissions per capita includes Australia and Ireland. With the exception of China, Australia and Ireland, there is a clear tendency for developed countries to have higher carbon prices and lower CO_2 emissions per capita than developing countries. In Figure 5b, as a function of GDP per capita measured in PPP, all developed countries were placed in the two quadrants showing levels above the average of USD 39,130 cap/yr, and carbon prices in the average of USD 41.96/tCO_2e. In contrast, developing countries were positioned in the low GDP per capita quadrants, with carbon prices above and below the average for the set of publications. Thus, there is more variability in the data when we consider carbon prices and GDP per capita than when we consider prices and CO_2 emissions per capita. This would indicate the influence of these two variables on carbon prices, which can be confirmed by a regression analysis.

4.3 Carbon pricing modeling for Brazilian agriculture

After a comprehensive understanding of pricing methodologies and carbon price determinants, an estimate of carbon prices in Brazilian agriculture was sought. This was done using quantile estimation based on loss function minimization to minimize the heterogeneity of the verified methods, extrapolating the coefficients to Brazil. Table 4 shows statistical results for different quantiles of the conditional distribution of the dependent variable (carbon price). Model 1 showed the best fit, since the three criteria based on the likelihood function (Schwarz, Akaike and Hannan-Quinn) were lower when compared to the other models. Seven of the nine variables tested showed statistical significance (p-value < 0.001), with the exception of the variables natural logarithm of the amount of nitrogen excreted in animal manure per capita (*lnliv*) and natural logarithm of the use of machinery per 1,000 ha of agricultural land (*lnmach*). The tests performed to identify heteroscedasticity in quantile regression (Breusch-Pagan and White) did not show significant evidence of non-constant variability in the residuals. The test results were not statistically significant, thus indicating that heteroscedasticity is not a significant problem for the fitted model (model 1). The other models did not show satisfactory statistical fits.

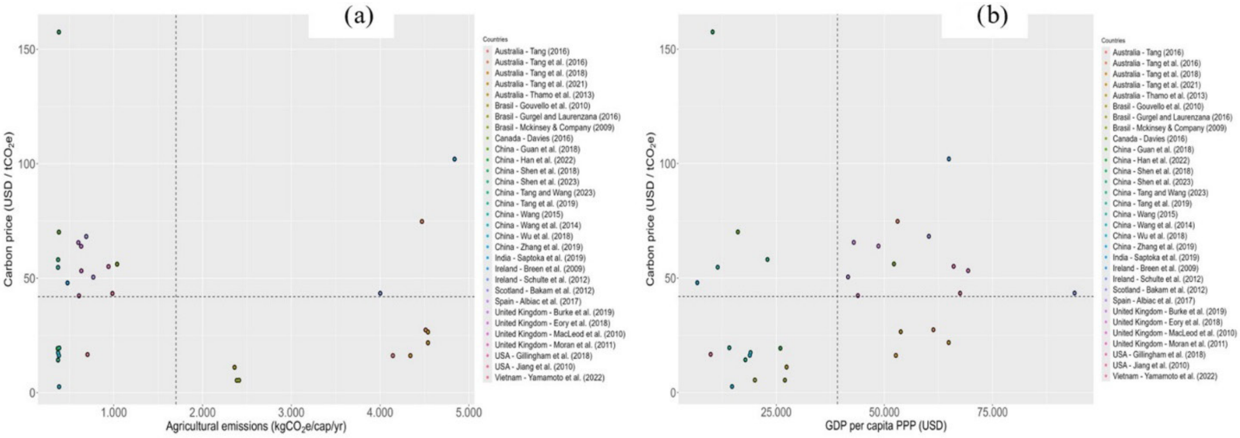

Figure 5. Relationship between carbon price and agricultural emissions (a) and carbon price and GDP per capita (b) Source: Carbon price was obtained from systematic literature review. Agricultural CO_2 emissions and GDP PPP were obtained from World Bank (2022), Food and Agriculture Organization of the United Nations (2021) and International Monetary Fund (2022), Gillingham & Stock (2018), Davies, (2016), Han & Chen (2022), Macleod et al. (2010), Tang et al. (2016b, 2018, 2021), Thamo et al. (2013), Breen & Donnellan (2009), Eory et al. (2015).

Table 4. Quantile regression results.

Variable	Model 1		Model 2		Model 3		Model 4	
Constant	290.863 (8.75)	***	55.343 (195.31)		-35.649 (106.67)		276.005 (45.42)	***
lnGDP	-21.470 (0.90)	***	-25.319 (19.58)		19.057 (5.93)	***	-63.002 (11.33)	
lnCO$_2$	-19.457 (0.42)	***	44.342 (25.35)	*	-31.245 (18.66)		26.502 (6.85)	***
lnfert	19.900 (0.63)	***	39.885 (16.31)	**	19.031 (10.82)	*	-5.290 (3.42)	***
lnpest	3.751 (0.52)	***	-42.591 (10.83)	***	-6.715 (5.52)			
Agri	-6.184 (0.19)	***	-11.454 (4.16)	**				
Emp	0.698 (0.03)	***	0.0775 (0.73)					
Land	1.063 (0.02)	***	-0.0620 (0.55)					

Source: Elaborated by the authors. *** p-value < 0.001 ** p-value < 0.01 * p-value < 0.05. The standard errors are in parentheses.

Variable	Model 1	Model 2		Model 3	Model 4	
lnliv		-55.810 (23.34)	**	5.522 (14.75)	30.155 (8.20)	***
lnmach		-19.403 (6.96)	**	-1.583 (5.03)	-5.887 (3.18)	*
Criterion						
Schwarz	321.963	324.113		322.509	324.744	
Akaike	310.237	311.456		312.248	315.950	
Hannan-Quinn	314.124	314.314		315.649	318.865	
Price for Brazil (Model 1) – USD 11.54/tCO_2e						

Source: Elaborated by the authors. *** p-value < 0.001 ** p-value < 0.01 * p-value < 0.05. The standard errors are in parentheses.

The results showed that GDP (*lnGDP*) is negatively correlated with carbon estimates, indicating that as this variable increases, there is less of a tendency to value carbon. Thus, countries with higher GDP economies have a lower abatement curve, and a 1% increase in GDP reduces the carbon price by USD 0.2147/tCO_2e. The estimated coefficient on carbon emissions has a negative sign: a 1% increase in CO_2 emissions per capita reduces the carbon price by USD 0.1945/tCO_2e. In economies in which CO_2 emissions tend to be higher, carbon price values may be lower, with less pressure on the demand for carbon credits. In addition, if CO_2 emissions increase, there may be less efforts to reduce emissions and fewer resources to invest in research and development of mitigation technologies. Similarly, countries with more active agriculture tend to have lower estimates of carbon valuation, as indicated by the negative relationship (-6.184). This result is corroborated by Smith et al. (2008), who pointed out that in regions where agriculture is of significant economic importance, the estimates for carbon valuation may be low due to the lack of effective policies and incentives to reduce emissions in agriculture. In the absence of financial or regulatory incentives to adopt more sustainable practices, farmers may not have sufficient incentive to invest in technologies and techniques that reduce their carbon emissions. The other regression coefficients (*lnfert, lnpest, emp, land*) showed positive relationship with carbon price, and a 1% increase in the natural logarithm of fertilizer use per capita would increase the value of carbon by USD 0.199/tCO_2e. The smallest effect could be attributed to the share of employment in agriculture: a 1% increase in this variable would increase the value of carbon by only USD 0.006/tCO_2e.

Considering the coefficients of the quantile regression for the set of publications, the estimated carbon price for Brazilian agriculture in 2021 was USD 11.54 /tCO_2e. There is a clear disparity between the carbon price in Brazilian agriculture and in some developed countries, as shown in Figure 5. However, Søndergaard et al. (2021) point out that prices above USD 10/tCO_2e serve as an important benchmark to stimulate mitigation efforts. Thus, the estimate obtained highlights the potential for Brazilian agriculture. Very few studies have estimated the value of carbon in Brazilian agriculture, out of which three stand out (Gurgel & Laurenzana, 2016; Gouvello et al., 2010; McKinsey & Company, 2009). These studies demonstrate carbon prices of USD 5.41/ tCO_2e, USD 11.09/tCO_2e, and USD 5.37/tCO_2e, respectively, in terms of constant 2017 prices.

Carbon pricing initiatives serve to internalize environmental expenses and foster the uptake of cleaner technologies and sustainable production methods. This parameter for Brazilian agriculture is relevant to guide policies and strategies adapted to local specificities. However, it is important to highlight the limitations of this study, including the need to integrate additional variables that might influence carbon values. Specifically, institutional factors such as price barriers and incentives for agricultural and livestock producers to embrace low-carbon practices, alongside cultural elements affecting farmers' willingness and capacity to adopt sustainable production systems, should be considered (Søndergaard et al., 2021). Other determinants could also be explored, such as total factor productivity for crops, use of energy and materials within a circular economy.

5. CONCLUSIONS

The global agricultural sector, which includes both crops and livestock, is a significant emitter of carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH4), gases with significant global warming potential. According to Food and Agriculture Organization of the United Nations (2023), more than one-third of global agricultural emissions come from the global food system. Carbon pricing has emerged as a tool to mitigate these emissions, and discussions mainly revolve around the implementation of a carbon tax or the adoption of a cap-and-trade system by economies. Academic and policy discourse has increasingly focused on whether the agricultural sector should be included in carbon pricing frameworks within emissions trading schemes (Stepanyan et al., 2023).

The objective of this article was to assess carbon pricing in agriculture by examining the methodologies used, the prices achieved, and the factors influencing these prices from 2004 to 2024. This article fills this gap by systematically synthesizing the evidence on carbon pricing and applying the integrated results of the review to the Brazilian agricultural context. In practical terms, the establishment of a reference value for the price of carbon in Brazilian agriculture is another gap that the study fills, providing a solid basis for the development of specific policies and strategies. Using the Page et al. (2021) methodology, the set of publications included integrated valuation models, carbon abatement cost analysis, shadow pricing techniques, and models integrating programming and optimization. Taking into account countries at different levels of development, the carbon prices identified in this study range from USD 2.60/tCO_2e to USD 157.50/tCO_2e, with values deflated to the year 2021. Notably, China accounts for one-third of the 32 publications analyzed. This research has identified several determinants that influence the price of carbon in agriculture, notably highlighting in particular the impact of GDP per capita, emissions per capita levels, and fertilizer use per capita on this valuation.

A review of existing methodologies provided a broad background for the study and clarified global practices for estimating carbon prices. Due to the variability among these methodologies, a quantile regression approach was then applied to the Brazilian context. It is important to clarify that methods such as marginal abatement cost and general equilibrium models are tools traditionally used for carbon pricing. On the other hand, quantile regression is not a carbon pricing method, but rather a statistical technique that allowed to extrapolate values for Brazil by avoiding the presence of heterogeneity. The estimated carbon price for Brazilian agriculture in 2021 was USD 11.54/tCO_2e at constant 2017 prices. There is a gap between the cost of carbon in agriculture for some developed countries and the estimates calculated for Brazil. Nevertheless, carbon prices above USD 10/tCO_2e are highlighted as a critical threshold to encourage mitigation efforts (Søndergaard et al., 2021). This estimate puts a cost on carbon emissions and encourages farmers to look for more efficient and less carbon-intensive ways of doing things. Comparison of carbon prices can help guide assessment strategies in agriculture. However, pricing alone may not be sufficient to promote a full transition to a low-carbon economy. Other measures, such as investment in research and development of clean technologies, may be needed to stimulate innovation and reduce the cost of climate solutions (Stern, 2007). In this sense, Brazil has made some progress in its national climate policy. In 2010, the country promoted the adoption of the Low Carbon Agriculture Plan (Plano ABC), which included several measures to support mitigation efforts in Brazil's agricultural sector. The updated version, Plano ABC+, was launched in 2021. In addition, the Brazilian Forest Code was revised in 2012 and Law No. 14.119/21, which regulates payments for environmental services, was launched in 2021.

Given the price variability observed within the same country, pilot projects analyzing carbon estimation methods across agricultural segments or regions could precede the establishment of regulations for the carbon market itself, with the aim of standardizing methodologies (Zhu et al., 2023). Selecting representative areas within a country to test and evaluate different carbon estimation methods under real-world conditions would facilitate direct comparisons and assess their effectiveness and feasibility in different agricultural and regional contexts. Such evaluations are imperative, especially considering that the agricultural sector remains excluded from price regulation schemes in many economies. For example, the European Union's Emissions Trading Scheme has not included agricultural GHG emissions. This exclusion reflects the European Union's recognition of agriculture as a distinct economic sector that both contributes to and is vulnerable to climate change through its GHG emissions. Similarly, countries such as China and New Zealand have not included the agricultural sector in their emissions trading schemes (Verschuuren et al., 2023). In Brazil, the agricultural sector was excluded from Bill No. 2.148/2015, which seeks to regulate the carbon market, due to the significant challenges posed by the specificities of the sector. These factors suggest that carbon pricing in agriculture is an important tool to support government decision-making, and requires appropriate measurement methodologies in different contexts. In the future, pilot projects and standardized methodologies can pave the way for the integration of agriculture into carbon pricing frameworks, providing a pathway towards sustainable and resilient agricultural practices.

Authors' contributions

DTS: Conception/design of the study, Data collection, Analysis and interpretation, Writing of the manuscript, and Critical review. FAPP: Analysis and interpretation; Writing of the manuscript. LRNJ: Writing of the manuscript, and Critical review. PGCF: Writing of the manuscript, and Critical review. CCR: Writing of the manuscript, and Critical review.

Financial support:

Nothing to declare.

Conflicts of interest:

Nothing to declare.

Ethics approval:

Nothing to declare.

Data availability:

The survey data (Embrapa Territorial, 2024) is available at the following link https://paineis.cnpm.embrapa.br/en_carbon_price/

*** Corresponding author:**

Daniela Tatiane de Souza. daniela.souza@embrapa.br

REFERENCES

Alsayed, A., Isa, Z., Kun, S., & Manzi, G. (2020). Quantile regression to tackle the heterogeneity on the relationship between economic growth, energy consumption, and CO2 emissions. *Environmental Modeling and Assessment*, *25*(2), 1-8. http://doi.org/10.1007/s10666-019-09669-7

Anthoff, D., Rose, S., Tol, R. S., & Waldhoff, S. (2011). Regional and sectoral estimates of the social cost of carbon: an application of Fund. *SSRN Electronic Journal*, *18*, 1-31. http://doi.org/10.2139/ssrn.1972778.

Baccour, S., Albiac, J., & Kahil, T. (2021). Cost-effective mitigation of greenhouse gas emissions in the agriculture of Aragon, Spain. *International Journal of Environmental Research and Public Health*, *18*(3), 1084. http://doi.org/10.3390/ijerph18031084

Bakam, I., Pajot, G., & Matthews, R. B. (2012). Estimating carbon price from a closed emissions trading scheme in the agricultural sector. *Journal of Land Use Science*, *7*(2), 221-238. http://doi.org/10.1080/1747423X.2011.563324

Bonesmo, H., Skjelvag, A. O., Henry Janzen, H., Klakegg, O., & Tveito, O. E. (2012). Greenhouse gas emission intensities and economic efficiency in crop production: A systems analysis of 95 farms. *Agricultural Systems*, *110*, 142-151. http://doi.org/10.1016/j.agsy.2012.04.001

Breen, J., & Donnellan, T. (2009). Estimating a marginal abatement cost curve for greenhouse gas emissions from Irish agriculture using farm-level data. In *Proceedings of the Annual Conference of the Agricultural Economics Society* (pp. 1-12). Cambridge: Agricultural Economics Society.

Burke, J., Byrnes, R., & Fankhhauser, S. (2019). *How to price carbon to reach net-zero emissions in the UK.* London, UK: London School of Economics and Political Science.

Campoli, J. S., & Feijó, J. R. (2022). *Preço do carbono para projetos de investimentos de infraestrutura no Brasil*. Brasília: Instituto de Pesquisa Econômica Aplicada.

Carvalho, M. M., Magalhães, A. S., & Domingues, E. P. (2022). *Mecanismos de precificação de carbono no Brasil: custos econômicos e potenciais de abatimento.* Rio de Janeiro: BNDES.

Davies, C. M. (2016). *Toward a low-carbon and climate resilient agriculture sector: policies to increase the adoption of cover crops in British Columbia*. Canada: Master of Public Policy.

Embrapa Territorial. (2024.). *Painel de preços de carbono.* Recuperado em 5 de dezembro de 2024, de https://paineis.cnpm.embrapa.br/en_carbon_price/

Eory, V., MacLeod, M., Faverdin, P., O'Brien, D., Oliveira Silva, R., Barioni, L. G., Albertini, T. Z., Topp, K., Fernandes, F. A., Moran, D., Hutchings, N., Stienezen, M., Shalloo, L., Rees, R. M., Mogensen, L., Lund, P., Brask, M., Doreau, M., Garcia-Launay, F., Dourmad, J.-Y., Bendahan, A. B., Veloso, R. F., & Sainz Gonzalez, R. D. (2015). *Report on developing bottom-up marginal abatement cost curves (MACCs) for representative farm types*. Paris: HAL Archives Ouvertes.

Eory, V., Pellerin, S., Carmona Garcia, G., Lehtonen, H., Licite, I., Mattila, H., Lund-Sørensen, T., Muldowney, J., Popluga, D., Strandmark, L., & Schulte, R. (2018). Marginal abatement cost curves for agricultural climate policy: state-of-the art, lessons learnt and future potential. *Journal of Cleaner Production*, *182*, 705-716. http://doi.org/10.1016/j.jclepro.2018.01.252

Estevam, C. G., Pavão, E. M., & Assad, E. (2023). *Quantificação das emissões de GEE no setor agropecuário: fatores de emissão, métricas e metodologias*. São Paulo: Fundação Getúlio Vargas.

Food and Agriculture Organization of the United Nations – FAO. (2021). *FAOSTAT statistical database.* Rome: FAO.

Food and Agriculture Organization of the United Nations – FAO. (2023). *Statistical yearbook: world food and agriculture 2023*. Rome: FAO.

Gillingham, K. K., & Stock, J. (2018). The cost of reducing greenhouse gas emissions. *The Journal of Economic Perspectives*, *32*(4), 53-72. http://doi.org/10.1257/jep.32.4.53

Gouvello, C., Soares Filho, B. S., Nassar, A., Schaeffer, R., Alves, F. J., & Alves, J. W. S. (2010). *Brazil low-carbon country case study*. Washington, DC: The International Bank for Reconstruction and Development/The World Bank.

Grosjean, G. (2017). *Reforming the European Union Emissions Trading System (EU ETS): an institutional perspective.* Berlin: Universität Berlin.

Guan, X., Zhang, J., Wu, X., & Cheng, L. (2018). The shadow prices of carbon emissions in China's planting industry. *Sustainability*, *10*(3), 1-12. http://doi.org/10.3390/su10030753

Gurgel, A. C., & Laurenzana, R. D. (2016). Desafios e oportunidades da agricultura brasileira de baixo carbono. In J. E. R. Vieira Filho, J. G. Gasques & A. X. Ywata de Carvalho (Eds.), *Agricultura, transformação produtiva e sustentabilidade* (pp. 311–330). Brasília, DF: Instituto de Pesquisa Econômica Aplicada.

Hafstead, M. A. C., Kopp, R. E., & Preston, B. L. (2021). The role of alternative market mechanisms in reducing greenhouse gas emissions. *Annual Review of Resource Economics*, *13*(1), 347-372.

Han, W., & Chen, W. Y. (2022). Embedding nature-based solutions into the social cost of carbon. *Environment International*, *167*, 107431. http://doi.org/10.1016/j.envint.2022.107431

International Monetary Fund. (2022). *Inflation rate, average consumer prices - annual percent change.* IMF.

Kumara, K., Pal, S., Chand, P., & Kandpal, A. (2023). Carbon sequestration potential of agroforestry systems in Indian agricultural landscape: a meta-analysis. *Ecosystem Services*, *62*, 101537.

Macleod, M., Moran, D., Eory, V., Rees, R. M., Barnes, A., Topp, C. F. E., Ball, B., Hoad, S., Wall, E., McVittie, A., Pajot, G., Matthews, R., Smith, P., & Moxey, A. (2010). Developing greenhouse gas marginal abatement cost curves for agricultural emissions from crops and soils in the UK. *Agricultural Systems*, *103*(4), 198-209. http://doi.org/10.1016/j.agsy.2010.01.002

Malange, R. (2015). An introduction to systematic reviews that include meta-analyses for Policy Makers and Analysts. *Revista Agenda Política*, *3*(2), 131-155.

McKinsey & Company. (2009). *Pathways to a low-carbon economy.* New York: McKinsey & Company.

McManus, C., Neves, A., Filho, J., Pimentel, F., & Pimentel, D. (2023). Funding as a determinant of citation impact in scientific papers in different countries. *Anais da Academia Brasileira de Ciências*, *95*(1), e20220515. http://doi.org/10.1590/0001-3765202320220515

Moran, D., MacLeod, M., Wall, E., Eory, V., McVittie, A., Barnes, A., Rees, R. M., Topp, C. F. E., Pajot, G., Matthews, R., Smith, P., & Moxey, A. (2011). Developing carbon budgets for UK agriculture, land-use, land-use change and forestry out to 2022. *Climatic Change*, *105*(3-4), 529-553. http://doi.org/10.1007/s10584-010-9898-2

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(7), 1518-1523. http://doi.org/10.1073/pnas.1609244114

Page, M. J., Mckenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P., & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, *372*(71), n71. http://doi.org/10.1136/bmj.n71

Raihan, A., Voumik, L. C., Mohajan, B., Rahman, M. S., & Zaman, M. R. (2023). Economy-energy-environment nexus: the potential of agricultural value-added toward achieving China's dream of carbon neutrality. *Carbon Res.*, *2*(43), 43. http://doi.org/10.1007/s44246-023-00077-x

Ranson, M. (2020). The political economy of carbon pricing policy design: insights from Canadian policymaking. *Review of Environmental Economics and Policy*, *14*(1), 56-75.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., & Smith, J. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *363*(1492), 789-813. http://doi.org/10.1098/rstb.2007.2184

Søndergaard, N., Dias de Sá, C., & Barros-Platiau, A. F. (2021). *Brazilian agriculture in a world of carbon pricing: challenges and opportunities* (Policy Paper). Brasília: Insper, Global Agribusiness Center.

Stepanyan, D., Heidecke, C., Osterburg, B., & Gocht, A. (2023). Impacts of national vs European carbon pricing on agriculture. *Environmental Research Letters*, *18*(7), 18. http://doi.org/10.1088/1748-9326/acdcac

Stern, N. (2007). *The economics of climate change: the Stern review.* Cambridge: Cambridge University Press. http://doi.org/10.1017/CBO9780511817434.

Tang, K. (2016). *Economic analysis of the potential for greenhouse gas mitigation through carbon farming in Australia's broadacre agricultural sector*. Australia: University of Western Australia.

Tang, K., & Wang, D. (2023). Cost-effectiveness of agricultural carbon reduction in China. In K. Tang & D. Wang (Eds.), *Carbon-neutral pathways for China: economic issues* (pp. 81-94). Singapore: Springer Nature Singapore.

Tang, K., Kragt, M. E., Hailu, A., & Ma, C. (2016a). Carbon farming economics: what have we learned? *Journal of Environmental Management*, *172*, 49-57. http://doi.org/10.1016/j.jenvman.2016.02.008

Tang, K., Hailu, A., Kragt, M. E., & Ma, C. (2016b). Marginal abatement costs of greenhouse gas emissions: broadacre farming in the Great Southern Region of Western Australia. *The Australian Journal of Agricultural and Resource Economics*, *60*(3), 459-475. http://doi.org/10.1111/1467-8489.12135

Tang, K., Hailu, A., Kragt, M. E., & Ma, C. (2018). The response of broadacre mixed crop-livestock farmers to agricultural greenhouse gas abatement incentives. *Agricultural Systems*, *160*, 11-20. http://doi.org/10.1016/j.agsy.2017.11.001

Tang, K., Wang, M., & Zhou, D. (2021). Abatement potential and cost of agricultural greenhouse gases in Australian dryland farming system. *Environmental Science and Pollution Research International*, *28*(17), 21862-21873. http://doi.org/10.1007/s11356-020-11867-w

Thamo, T., Kingwell, R. S., & Pannell, D. J. (2013). Measurement of greenhouse gas emissions from agriculture: economic implications for policy and agricultural producers. *The Australian Journal of Agricultural and Resource Economics*, *57*(2), 234-252. http://doi.org/10.1111/j.1467-8489.2012.00613.x

Tol, R. S. J. (2024). A meta-analysis of the total economic impact of climate change. *Energy Policy*, *185*, 113922. http://doi.org/10.1016/j.enpol.2023.113922

United Nations. (2020). *Nationally determined contributions (NDCs): the Paris Agreement and NDCs*. Bonn: United Nations Framework Convention on Climate Change.

United States Department of Agriculture. (2019). *International agricultural productivity*. Washington, D.C.: United States Department of Agriculture.

Vermont, B., & Cara, S. D. (2010). How costly is mitigation of non-CO2 greenhouse gas emissions from agriculture? A meta-analysis. *Ecological Economics*, *69*(7), 1373-1386. http://doi.org/10.1016/j.ecolecon.2010.02.020

Verschuuren, J., Fleurke, F., & Leach, M. (2023). *Policy brief integrating agricultural emissions into the EU ETS*. Tilburg, Netherlands: Tilburg University.

Wang, J., Li, L., Zhang, F., & Xu, Q. (2014). Carbon emissions abatement cost in China: provincial panel data analysis. *Sustainability (Basel)*, *6*(5), 2584-2600. http://doi.org/10.3390/su6052584

Wang, P., Deng, X., Zhou, H., & Yu, S. (2019). Estimates of the social cost of carbon: a review based on meta-analysis. *Journal of Cleaner Production*, *209*, 1494-1507. http://doi.org/10.1016/j.jclepro.2018.11.058

Wang, R., Li, T., & Zhu, J. (2022). Evaluating the agricultural carbon shadow price in countries along the Belt and Road Initiative: a by-production process. *Journal of Global Information Management*, *30*(6), 1-16. http://doi.org/10.4018/jgim.302656

Wang, W. (2015). *Integrating agriculture into the Chinese mitigation policies.* Paris, France: Docteur en Sciences Economiques, Universite Paris-Dauphine.

Wooldridge, J. M. (2023*). Introdução à econometria: uma abordagem moderna*. São Paulo: Cengage Learning.

World Bank. (2022). *World Development Indicators.* Washington, DC: World Bank.

Yamamoto, A., Huynh, T. K. U., Saito, Y., & Matsuishi, T. F. (2022). Assessing the costs of GHG emissions of multi-product agricultural systems in Vietnam. *Scientific Reports*, *12*(1), 1-12. http://doi.org/10.1038/s41598-022-20273-w

Zhu, B., Jia, T., Zhang, T., & Liu, C. (2023). Cities' marginal carbon abatement costs heterogeneity and the potential benefits from emission trading schemes in the Yangtze River Delta Region. *Environment, Development and Sustainability*, http://doi.org/10.1007/s10668-023-03872-z

Received: July 10, 2024;
Accepted: September 28, 2024
JEL Classification: Q1 and Q5

Associate Editor: Silvio Cezar Arend