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The spatial distribution of agricultural emissions in the United States: The role of organic farming in mitigating climate change

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ABSTRACT

Agriculture is a significant contributor to greenhouse gas (GHG) emissions and organic farming practices can potentially offset some of these emissions. However, previous research on the environmental impact of organic agriculture has provided mixed or contradictory results. This study aims to analyze the role that organic farming can play in mitigating agricultural emissions across the United States. Using panel U.S. state-level data, we find evidence that farming activities increase GHG emissions. However, we also find that dedicating a larger share of farmland to organic and pasture farming reduces GHG emissions. A spatial analysis of agricultural emissions that accounts for the role of organic farming provides three key insights. First, the spatial distribution of agricultural GHG emissions in the United States is uneven. Second, agriculture is a significant contributor to GDP within high-emissions states where organic agriculture represents only a small proportion of total farmland. Third, agriculture has a substantially lower contribution to GDP within low-emissions states where organic agriculture represents a large proportion of total farmland. These findings suggest that reducing GHG emissions effectively may necessitate creating and implementing policies and initiatives tailored to specific regions rather than relying on general recommendations. Thus, low-emissions states should be explored as examples of sustainable agricultural practices that could set the stage for scaling up organic farming practices across the country.

1. Introduction

Greenhouse gas (GHG) emissions have been steadily increasing worldwide due to relentless consumption of fossil fuels, deforestation, and other human activities. The three largest sectors responsible for GHG emissions are energy use in industry, responsible for 24.2% of emissions, followed by agriculture, forestry, and land use at 18.4%, and energy use in buildings at 17.5% (Ritchie et al., 2020). Significant strides have been made toward transitioning to renewable energy sources with 95% of the growth in global power capacity projected to come from renewables by 2026 (International Energy Agency, 2021). Commercial buildings worldwide have also contributed to decarbonization efforts, with total avoided emissions of 4,375 metric tons of CO_{2e} across 16 major countries between 2010 and 2019 and representing 10% of total cumulative emissions (Xiang et al., 2022). With the United States and China being the top carbon-emitting countries, deeper and more drastic decarbonization efforts can allow these countries to achieve carbon neutrality in commercial buildings by 2060 (Zhang et al., 2022). In contrast, agricultural decarbonization has lagged with emissions projected to decrease in the European Union, for instance, by only about 1.5% between 2020 and 2040 (European Environment Agency, 2022).

While significant progress has been made in decarbonizing energy use in industry and commercial buildings and possibly other sectors, there is still much work to be done to tackle emissions from agriculture. To address this concern, the Conference of the Parties (COP23) adopted in its 23rd session held in 2017 decision 4/CP.23 on the "Koronivia joint work on agriculture" calling for the Subsidiary Body for Scientific and Technological Advice (SBSTA) and the Subsidiary Body for Implementation (SBI) to work together to address issues relating to agriculture and food security (UNFCCC, 2018). In the recent 27th session of the Conference of the Parties (COP27), which was held in Egypt in November 2022, participating countries acknowledged the necessity for a shift to food systems that are not only sustainable but also resilient to climate change. Special emphasis was placed

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on the use of organic fertilizers, improved manure management, and more sustainable livestock systems (UNFCCC, 2022). With agriculture, forestry, and land use contributing significantly to global emissions, the shift is expected to not only reduce global emissions but also to help alleviate world hunger and poverty. Thus, understanding the drivers of agricultural emissions can help identify effective means to reduce them. In particular, organic agricultural practices can offset some of these emissions or those from other sectors.

Organic agriculture has numerous environmental benefits. For instance, conventional farming techniques generally depend on chemical fertilizers, which can damage soil structure and deplete it of vital nutrients. This can lead to soil erosion and loss of fertility, thereby reducing crop yields and productivity. Organic farming has the opposite effect due to its reliance on natural fertilizers, such as compost and manure, which add nutrients to the soil and improve its structure. Organic farming also minimizes the use of synthetic chemicals, such as pesticides and herbicides, which can be harmful to the environment, human health, and wildlife and can contaminate the food, soil and water sources. Organic farming generally uses natural methods to control pests and weeds, such as crop rotation, green manure, compost, and the introduction of beneficial insects and natural predators (Niggli et al., 2009). These tools help soils get healthier and more resilient to extreme weather events, and promote biodiversity while also reducing the potential health risks associated with synthetic pesticides and herbicides. Organic agriculture can also sequester up to one third of the current emissions from the use of ecologically-sound processes to manage the land, soil, and crops (Jordan et al., 2009). More optimistic estimates put the sequestration potential at 40%–72% from the elimination of mineral fertilizers, reduced energy use, and sequestration from croplands and grasslands (Scialabba and Müller-Lindenlauf, 2010).

While organic agriculture appears to be a promising tool to be used in tackling climate change, supporting evidence has been based on a large number of lifecycle analyses (LCAs) contrasting organic and conventional agriculture. These studies have yielded estimates that varied greatly across goods, categories of goods, regions, and sometimes even across studies covering the same goods or categories. In general, compared to conventional agriculture, organic agriculture has been estimated to use less energy per unit of land (Gomiero et al., 2008; Tuomisto et al., 2012; Clark and Tilman, 2017), to emit less GHG emissions per unit of land (Mondelaers et al., 2009; Tuomisto et al., 2012), to leach less nitrate (Mondelaers et al., 2009; Tuomisto et al., 2012), to emit less ammonia per unit of land (Tuomisto et al., 2012), to contain more soil organic matter (Mondelaers et al., 2009; Tuomisto et al., 2012), and to have more enhanced biodiversity (Bengtsson et al., 2005; Tuck et al., 2014). On the other hand, conventional agriculture has been estimated to use more energy per unit of output (Gomiero et al., 2008), to emit less N_2O per unit of output (Tuomisto et al., 2012), to leach less nitrate when measured globally (Mondelaers et al., 2009), to emit less ammonia per unit of output (Tuomisto et al., 2012), and to have lower eutrophication and acidification potential per unit of output (Clark and Tilman, 2017).

The mixed results and measurement issues in LCAs suggest that further research using alternative methods, such as regression analysis, is needed. In fact, the subjectivity in data selection and restrictive assumptions in LCAs raise questions about the certainty of these findings and limit their generalizability. In addition, studies using regression analysis have been limited to two studies that add more to the ambiguity delivered by LCAs, with one presenting evidence of a positive association between organic farming and GHG emissions (McGee, 2015) and another finding a negative relationship (Squalli and Adamkiewicz, 2018).

The ambiguity resulting from previous research creates a significant knowledge gap regarding the environmental impact of organic agriculture. This paper aims to fill this gap by estimating and mapping GHG emissions from agriculture across the United States, taking into account the role of organic agriculture. This is a significant contribution as it is the first attempt to account for the role of organic agriculture in reducing GHG emissions in a spatial depiction of emissions. The research aims to identify patterns across states according to identifiable characteristics, allowing policymakers to better target their efforts to reduce emissions and assess the impact of organic agriculture on GHG emissions. To this end, this paper is organized as follows: Section 2 summarizes previous relevant research. Section 3 describes the data and methodology. Section 4 summarizes the estimation results. Section 5 discusses the spatial distribution of emissions. Section 6 discusses the findings and concludes.

2. Previous research

Although the general consensus is that organic farming is more environmentally sustainable than its conventional counterpart, previous research has not provided categorical supporting evidence. Various LCAs have compared conventional and organic farming across a number of categories, including but not limited to land use, energy use, GHG emissions, nutrient leaching, soil quality, and biodiversity. The following represents a summary of some relevant contributions.

2.1. Energy use

A review of several studies comparing conventional to organic agriculture found that the latter used 10%–70% less energy per unit of land for all analyzed crops, 8%–54% less energy per unit of output for most crops, and 23% more energy per unit of output for apples and up to 29% more energy per unit of output for potatoes (Gomiero et al., 2008). In another meta-analysis, organic agriculture was found to use on average 21% less energy per unit of output across a range of products except for pork and potatoes, which showed more energy use (Tuomisto et al., 2012). The higher energy use was attributed to significant crop and feed production for pork (Basset-Mens and Van der Werf, 2005) and to the deep ploughing that potatoes typically require in cultivation and during harvest (Glendining et al., 2009).

2.2. GHG emissions

The meta-analysis by Tuomisto et al. (2012) found GHG emissions to vary across different products. For instance, organic olive, beef, and other crops had lower GHG emissions, whereas organic milk, cereals, and pork had greater emissions. Lower emissions for olives were attributed to a lower consumption of fossil fuels, whereas those for beef were attributed to industrial inputs (Casey and Holden, 2006). On the other hand, the greater emissions from organic milk and pork were caused by high methane and nitrous oxide emissions from straw litter (Thomassen et al., 2008). These mixed findings led to the conclusion that GHG emissions per unit of output did not vary across conventional and organic agriculture. In contrast, another meta-analysis conducted by Mondelaers et al. (2009) found GHG emissions per unit of land to be 39% lower in organic farms and 10% lower per unit of output.

Tuomisto et al. (2012) found that nitrous oxide emissions were about 31% lower per unit of land but 8.5% higher per unit of output in organic farms. Mondelaers et al. (2009) estimated the lower nitrous oxide emissions in organic farms to be only 14% per unit of land and provided no estimates for the changes in emissions per unit of output.

2.3. Nutrient leaching

The leaching of nutrients in organic agriculture, which can represent a major source of acidification, eutrophication, and groundwater contamination, varies depending on whether it is measured per unit of land or per unit of output. For instance, Tuomisto et al. (2012) estimated nitrate leaching to be 30.6% lower per unit of land, consistent with the 29.7% rate estimated by Mondelaers et al. (2009). However, on a per unit of output basis, Tuomisto et al. (2012) estimated nitrate leaching

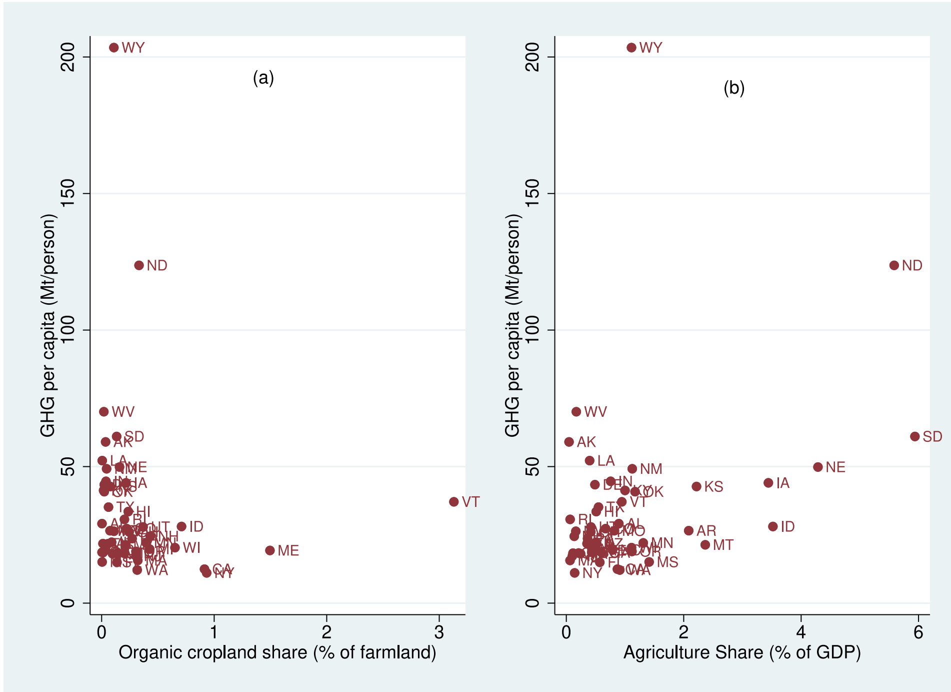

Fig. 1. Scatter plots of organic cropland, farming share, and GHG emissions.

in organic agriculture to be 49.1% higher, while (Mondelaers et al., 2009) estimated it to be 5% lower. Tuomisto et al. (2012) attributed the lower nitrogen level to fewer nitrogen input applications and the higher nitrogen level to a mismatch between nitrogen availability and a crop's nitrogen intake. The study also suggested that lower nitrogen leaching per unit of product arose from the use of cover crops in organic farming.

Ammonia emissions were also estimated to be 18% lower per unit of land but 11% higher per unit of output (Tuomisto et al., 2012). Furthermore, in a more recent meta-analysis, organic agriculture was estimated to raise the eutrophication and acidification potential per unit of output by 36% and 13%, respectively (Clark and Tilman, 2017).

2.4. Soil quality and biodiversity

According to Tuomisto et al. (2012) and Mondelaers et al. (2009), soil organic matter levels were found to be over 6% higher in organic farms due to increased inputs of organic matter such as manure and compost. In a meta-analysis focusing on biodiversity and abundance, Bengtsson et al. (2005) showed that organic agriculture could increase species richness by an average of 30%. This estimate was further confirmed in an updated meta-analysis (Tuck et al., 2014). Organic agriculture was also estimated to increase organism abundance by an average of 50% (Bengtsson et al., 2005). However, Bengtsson et al. (2005) found significant variability across studies with 16% of them showing a negative effect of organic farming on species richness. Furthermore, there were no clear benefits observed in studies focused on non-predatory insects and pests as well as in farms with matched landscapes.

These studies represent a small example of how useful LCAs are in evaluating the environmental impact of different agricultural practices. However, there are also less common methods, such as regression analysis, which can provide insights into the impact of organic farming on GHG emissions. To date, only two relatively recent studies used regression analysis to examine this issue. The first study by McGee (2015) found that organic farming increased GHG emissions. They attributed this effect to the "displacement paradox", which suggests that the expansion of the organic farming sector does not always replace conventional farming, but rather represents new demand. In contrast, the second study by Squalli and Adamkiewicz (2018), found that organic farming could reduce GHG emissions and attributed the effect to organic farming practices, such as regenerative farming and distribution into local markets.

It is worth mentioning that previous evidence measuring the impact of organic agriculture per unit of output seemed to be based on the assumption that yield gaps between organic and conventional agriculture were large and constant, typically around 20%–25% (De Ponti et al., 2012; Seufert et al., 2012), when in fact they have been estimated at around 19.2% (Ponisio et al., 2015) and could even be as low as 8%–9% (Stanhill, 1990; Badgley et al., 2007). Indeed, yield gaps between organic and conventional agriculture are likely decreasing as diversification methods such as multicropping and crop rotations are gradually being incorporated (Ponisio et al., 2015).

In sum, previous research raises three key points. First, the mixed results in LCAs and discrepancies between the findings of McGee (2015) and Squalli and Adamkiewicz (2018) highlight the lack of categorical supporting evidence for the general expectation that organic farming is more environmentally sustainable than conventional farming. Second, the mixed results represent a knowledge gap that can be filled with further research. Third, the implication is that the environmental sustainability of farming practices is a complex issue that requires a fresh look. This study addresses these points by making use of regression analysis to develop an understanding of the role that organic agriculture can play in mitigating GHG emissions.

3. Methods

3.1. Data

We make use of U.S. state-level data over the 1997–2010 period. However, due to missing data from the USDA, we exclude the years

Table 1
Summary statistics.

Variables		Max	Min	SD	Mean	Obs.
ln GHG	Overall	6.7	2.3	0.79	4.63	N = 550
	Between	6.68	2.99	0.79		n = 50
	Within	5.12	2.88	0.14		T = 11
ln population	Overall	17.44	13.1	1.01	15.09	N = 550
	Between	17.38	13.15	1.02		n = 50
	Within	15.26	14.83	0.05		T = 11
ln income	Overall	11.17	10.25	0.18	10.68	N = 550
	Between	11.05	10.32	0.17		n = 50
	Within	10.98	10.41	0.06		T = 11
ln VMT	Overall	12.7	8.39	0.98	10.52	N = 550
	Between	12.67	8.49	0.99		n = 50
	Within	10.74	10.21	0.06		T = 11
Oil & natural gas (% of GDP)	Overall	38.05	0	3.91	1.5	N = 511
	Between	19.54	0	3.66		n = 50
	Within	20.01	−3.79	1.11		T = 10.2
Utilities (% of GDP)	Overall	4.37	0.61	0.63	2.12	N = 550
	Between	3.51	0.69	0.57		n = 50
	Within	3.08	1.22	0.28		T = 11
Manufacturing (% of GDP)	Overall	29.81	1.75	5.48	12.46	N = 550
	Between	27.24	1.97	5.34		n = 50
	Within	26.13	4.43	1.42		T = 11
Transportation (% of GDP)	Overall	11.79	1.34	1.51	3.3	N = 550
	Between	9.97	1.43	1.5		n = 50
	Within	5.13	1.79	0.28		T = 11
ln farmland	Overall	18.69	11	1.57	15.95	N = 550
	Between	18.69	11.11	1.59		n = 50
	Within	16.1	15.84	0.03		T = 11
ln organic cropland	Overall	13.12	0.69	2.26	9.01	N = 535
	Between	12.27	4.73	2.18		n = 50
	Within	13.24	3.52	0.77		T = 10.7
ln organic pasture	Overall	14.19	1.61	2.53	7.88	N = 456
	Between	13.03	3.43	2.37		n = 50
	Within	11.93	2.39	1.16		T = 9.12
ln organic crop × Transportation	Overall	98.81	0.95	14.84	29.84	N = 535
	Between	86.39	6.75	14.56		n = 50
	Within	46.7	−5.3	3.87		T = 10.7

1998, 1999, and 2009. Although the USDA reports its last year of data for organic acreage as 2011, there is no matching data for total farming acreage, which is available for 2012 and 2017. To our knowledge, there is no similar data at a lower level of aggregation. Emissions data are from the World Resources Institute's (WRI) CAIT-US. We limit our analysis to total greenhouse gas (GHG) emissions, which are measured in metric tons of CO_2 equivalent (MTCE). In particular, GHG data account for land-use change and forestry (LUCF), which account for carbon emissions and carbon sinks arising from deforestation, reforestation, and land use changes. According to the Environmental Protection Agency, GHG emissions are comprised of 79% CO_2, 11% CH_4, 7% N_2O, and 3% fluorinated gases (i.e. hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3)).[1]

Other data include real per capita GDP (in chained 2009 dollars), output share for utilities, manufacturing, oil and natural gas, and transportation (% of state GDP), which are from the Bureau of Economic Analysis. Data for vehicle miles traveled (VMT) are from the U.S. Department of Transportation's Federal Highway Administration, whereas those for organic cropland acreage, organic pasture acreage, and total farmland acreage are from the USDA's Economic Research Service. Finally, data for population, which represent mid-year estimates are from the U.S. Census Bureau.

[1] Source: Environmental Protection Agency, https://www.epa.gov/ghgemissions/overview-greenhouse-gases

Table 1 presents summary statistics of all variables. Upon close inspection, we can see that the variation in most of these variables differs significantly across states compared to within a state over time. This suggests that using panel analysis is appropriate since the listed variables are influenced by variation across both states and time.

Fig. 1 provides a preliminary look at the relationship between organic cropland (% of farmland) and GHG emissions per capita and the relationship between the share of agriculture (% of GDP) and GHG per capita, in panels (a) and (b), respectively. These figures are derived after averaging data for each state across time and scaling GHG data with the population variable. Panel (a) suggests a possible negative correlation between the share of organic cropland and per capita GHG emissions. However, due to the limited prevalence of organic farming across the United States, most data points are clustered near the origin, making it difficult to establish a clear pattern. On the other hand, panel (b) shows a positive correlation between the share of agriculture and GHG emissions per capita, which is not surprising given that agriculture is a major contributor to GHG emissions.

3.2. Empirical specifications

We assess the relationship between organic farming acreage and GHG emissions using a model based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) approach (e.g. Dietz and Rosa, 1994; York et al., 2003; Cole and Neumayer, 2004; Squalli, 2009, 2010, 2014). The STIRPAT model is based on the IPAT mathematical identity, which hypothesizes that environmental impact (I) is influenced by population (P), affluence (A), and technology (T), such that $I = P \times A \times T$ (Ehrlich and Holdren, 1971). The IPAT model can be expressed for U.S. state-level panel regression analyses as Eq. (1):

$$I_{it} = \alpha P_{it}^{\beta} A_{it}^{\gamma} T_{it}^{\delta} \epsilon_{it} \quad (1)$$

where i and t represent the state and period, respectively, whereas the constant terms are comprised of α, β, γ, and δ followed by the error term ϵ. After log-linearization, we get Equation (2):

$$\ln I_{it} = \ln \alpha + \beta \ln P_{it} + \gamma \ln A_{it} + \delta \ln T_{it} + \ln \epsilon_{it} \quad (2)$$

where β, γ, and δ can be interpreted as ecological elasticities, which measure the percent change in environmental impact (e.g. GHG emissions) in response to a one percent change in corresponding explanatory variables. It is worth noting that log transformation has several advantages. First, estimates with variables that have been log-transformed are less susceptible to outliers and heteroskedastic residuals. Second, the coefficient estimates, as ecological elasticities, assess how responsive a dependent variable is to independent variable changes when adjusted for other variables. In order to simplify economic interpretations and address potential concerns about inconsistent measurement units, changes are expressed in percentage terms rather than levels. Third, since log transformation scales the data to a standard unit of measurement, the interpretation of coefficient estimates is more accurate.

The base model for our analysis can be expressed by Eq. (3):

$$GHG_{it} = \alpha + \beta\ POP_{it} + \gamma\ INC_{it} + \delta\ TECH_{it} + \theta_i + \theta_t + \epsilon_{it} \quad (3)$$

where log GHG emissions for U.S. state i in period t are estimated with respect to log population (POP), a vector of income variables (INC), and a vector of technology variables (TECH). The model also has a state-specific component, θ_i, a year-specific component, θ_t, and an idiosyncratic shock, ϵ_{it}.

The population variable is a scale variable and controls for the well-known effect of population growth on emissions. The INC vector of variables is comprised of log real per capita GDP and the latter's squared term. Real per capita GDP is a proxy for affluence and is also introduced in a quadratic form to account for potential non-linearity between affluence and emissions, consistent with the Environmental Kuznets Curve hypothesis (Grossman and Krueger, 1995). The vector of technology variables (TECH) includes log vehicle miles traveled (VMT), output share of oil & natural gas (OIL), utilities (UTIL), manufacturing (MANUF), and transportation (TRANS) sectors (% of state GDP). The VMT variable controls for the potential effect of driving vehicles on GHG emissions. The OIL, UTIL, MANUF, and TRANS variables control for emissions from relatively large oil and natural gas production, manufacturing, utilities, manufacturing, and transportation sectors, respectively.

The augmented model, which adds variables related to farming activities, can be expressed by Eq. (4):

$$GHG_{it} = \alpha + \beta\ POP_{it} + \gamma\ INC_{it} + \delta\ TECH_{it} + \lambda\ FARM_{it} + \theta_i + \theta_t + \epsilon_{it} \quad (4)$$

where FARM represents a vector of variables comprised of log total farmland acreage (FARMLAND), log organic cropland acreage (ORGCROP), and log organic pasture acreage (ORGPAST). Furthermore, and consistent with Squalli and Adamkiewicz (2018), we include an interaction term between ln ORGCROP and TRANS.

Given our aim to assess the partial impact of organic agriculture on GHG emissions, we consider FARMLAND, ORGCROP, and ORGPAST as our key variables of interest. We expect their joint use to control for emissions arising from the agricultural sector and for the relative size of the organic farming sector. On the other hand, the interaction term between TRANS and ln ORGCROP helps interpret the effect of organic farming acreage for given levels of transportation output share. Given the importance of transportation to farming, this would help examine whether the potential environmental benefits of organic food production, if any, are substantial enough to outweigh the environmental harm of transportation output embodied in organic farming.

3.3. Estimation method

We estimate Equation (4) using random effects and fixed effects estimators and cluster-robust standard errors that control for arbitrary heteroskedasticity and arbitrary intragroup correlation. We use a Hausman test to choose an appropriate estimator and use a Wald test to determine the inclusion of year dummies. Once an appropriate estimator is selected, we derive estimates for the error term. The error component in random effects estimations is comprised of the state-specific component and the idiosyncratic shock, whereas the state-specific component is captured by the intercept in fixed effects estimations.

4. Estimation results

Table 2 summarizes the estimation results. Based on the Hausman test, we choose for our estimations random effects with cluster robust standard errors. We also focus on the estimations that exclude year dummies due to their higher explanatory power.[2] We estimate four specifications with the gradual introduction of the key variables, namely those representing farmland, organic cropland, and organic pasture. The results reported in column (1) are for the base STIRPAT specification with variables controlling for population, affluence, and technology. Column (2) shows the estimation results of the base STIRPAT model that is augmented with the farmland variable. Column (3) includes the estimation results of the specification in column (2) that is augmented with the organic cropland and organic pasture variables. Finally, the estimation results in column (4) are for the specification in column (3) that is augmented with the interaction variable of organic cropland and transportation.

The estimation results in column (1) of the base model show a bell-shaped relationship between income and GHG emissions and all other parameter estimates, except for population, are positive and statistically significant. The estimation results in column (2) show that with the introduction of the FARMLAND variable, the explanatory power of the model increases despite the smaller sample size of 656 observations instead of 700 observations in the base model. As expected and contrary to the base model's estimation results, the parameter estimate for population is positive and statistically significant. The nonlinear relationship between income and GHG emissions is unaffected in the new model and the variables Oil & Natural Gas, Utilities, Manufacturing, and log farmland have positive and statistically significant coefficient estimates (at least $p < 0.01$). The estimation results in column (3) are for the augmented model that includes the organic cropland and organic pasture variables. The sample size is reduced to 421 observations and the explanatory power increases slightly. Although there is no longer any evidence of a nonlinear relationship between income and GHG emissions, the remaining variables maintain their sign and statistical significance. In addition, the parameter estimates for organic cropland and organic pasture are negative and statistically significant ($p < 0.01$).

The estimation results in column (4) show that although most of the parameter estimates of the variables previously discussed and explanatory power of the model are unaffected by the new change, there is no evidence of a statistically significant interaction effect between transportation and organic cropland acreage. Nevertheless, given that the size of the coefficient estimate for organic cropland changes slightly, we can infer that the interaction term does play a role that is not necessarily captured from this model and would be likely captured when environmental impact is measured with other greenhouse gases (i.e. CH_4 and N_2O) as previously established by Squalli and Adamkiewicz (2018).

Focusing on the estimation results in column (4), we find that the parameter estimates for the variables of interest provide important

[2] R^2 values are higher for the estimations that exclude year dummies.

Table 2
Estimation results ($n = 50$).

VARIABLES	(1)	(2)	(3)	(4)
ln population	0.289 (0.189)	0.478* (0.193)	0.506** (0.160)	0.541*** (0.165)
ln income	34.323* (14.717)	34.545* (15.154)	22.032 (16.355)	22.139 (15.883)
(ln income)^2	−1.589* (0.684)	−1.591* (0.704)	−1.005 (0.759)	−1.012 (0.737)
ln VMT	0.324 (0.180)	0.091 (0.193)	0.080 (0.166)	0.042 (0.169)
Oil & Natural Gas	0.020* (0.008)	0.018* (0.008)	0.034*** (0.010)	0.035*** (0.010)
Utilities	0.097** (0.034)	0.106** (0.034)	0.081** (0.033)	0.068* (0.034)
Manufacturing	0.021*** (0.005)	0.020*** (0.006)	0.020** (0.006)	0.020** (0.006)
Transportation	0.049 (0.027)	0.034 (0.028)	0.038 (0.035)	−0.058 (0.055)
ln farmland		0.110** (0.038)	0.129** (0.038)	0.131*** (0.036)
ln organic cropland			−0.024* (0.011)	−0.059* (0.027)
ln organic pasture			−0.009* (0.004)	−0.007* (0.003)
ln organic cropland × Transportation				0.010 (0.007)
Constant	−189.083* (79.892)	−193.320* (82.290)	−126.810 (88.286)	−127.066 (85.718)
Hausman χ^2	12.94			
p value	0.37			
N	700	656	421	421
Overall R-squared	0.784	0.807	0.828	0.828

Notes: Cluster-robust standard errors in parentheses.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

insight on the environmental effect of agriculture. U.S. states that have more farmland have more GHG emissions ($p < 0.001$), whereas those that have more cropland dedicated to organic agriculture have lower GHG emissions ($p < 0.01$). In addition, those states that have organically-managed pasture have lower GHG emissions ($p < 0.01$). The reported parameter estimates represent ecological elasticities, which measure the percentage change in GHG emissions resulting from a one percent increase in farmland use. Based on these estimates, a one percent increase in total farmland acreage is estimated to increase GHG emissions by 0.131 percent, whereas a one percent increase in organic cropland acreage is estimated to decrease GHG emissions by about 0.06 percent, and a one percent increase in organic pasture acreage is estimated to decrease emissions by 0.007 percent.

Table 3
Bootstrapped standard errors of the key variables.

	Replications		
	500	1000	2000
ln farmland	0.0152 (0.000)	0.0148 (0.000)	0.0148 (0.000)
ln organic cropland	0.0207 (0.004)	0.0210 (0.005)	0.0208 (0.005)
ln organic pasture	0.0040 (0.063)	0.0039 (0.056)	0.0039 (0.055)

The cluster-robust bootstrapped standard errors are reported with their corresponding p values between parentheses.

4.1. Sensitivity analysis

The estimation results discussed above must be carefully scrutinized to ensure that they are not influenced by extreme observations. Outliers can significantly impact coefficient estimates and standard errors, thereby resulting in potentially inaccurate and unreliable interpretations of coefficient estimates. The bootstrap method can be used to re-estimate our model and produce more reliable parameter estimates that downweight the influence of extreme observations, if any (Wooldridge, 2010). For robustness, we combine cluster-robust estimation with resampling for our bootstrap.

Given the relatively small sample used in our analysis and the importance of obtaining reasonably precise estimates, we re-estimate Equation (4) using a random effects approach with cluster-robust standard errors and the following series of bootstrap replications: 500, 1000, and 2000. It is worth noting that although 500 replications would suffice, we choose to add an additional dimension of sensitivity analysis by evaluating the stability of our estimates across different numbers of replications.

Table 3 reports the cluster-robust bootstrapped standard errors of our key variables along with their p-values. Although we observe a decrease of the standard errors for both ln farmland and ln organic cropland, the parameter estimates for these two variables remain statistically significant. On the other hand, the standard error for ln organic pasture increases sufficiently to eliminate statistical significance. However, upon close inspection, we can see that the standard error in the original estimation is 0.0035, whereas the bootstrapped standard error

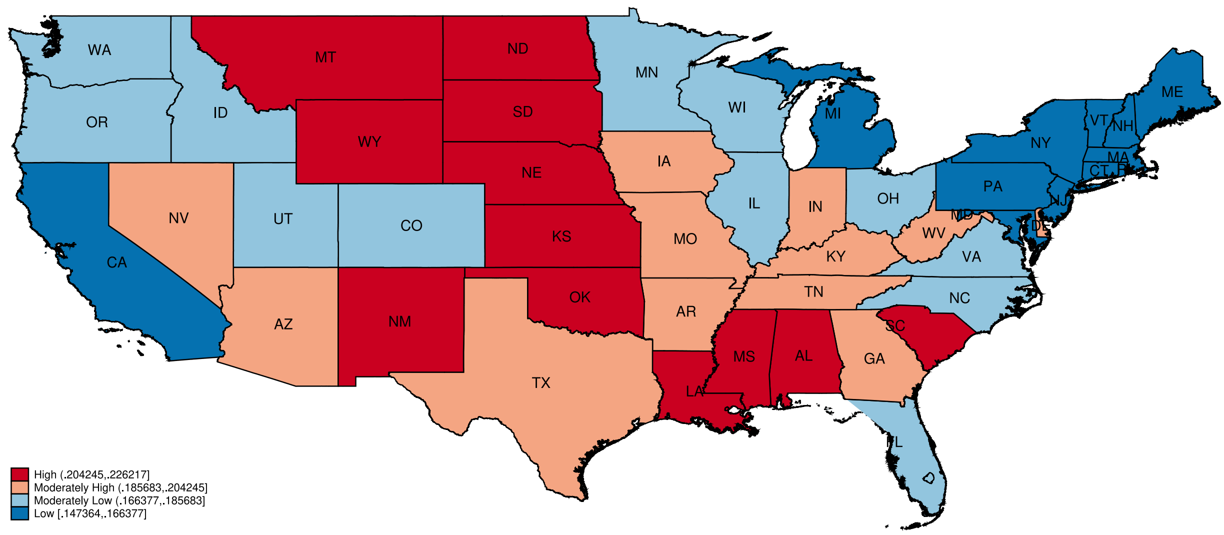

Fig. 2. Spatial distribution of GHG emissions (Quantiles).

Table 4
Estimates of GHG emissions from agriculture.

State	GHG	State	GHG
WY	0.226	NC	0.185
SD	0.217	CO	0.184
MS	0.215	UT	0.183
MT	0.212	ID	0.182
NM	0.211	OR	0.181
ND	0.211	IL	0.181
AL	0.211	MN	0.179
OK	0.208	VA	0.176
LA	0.208	WA	0.174
SC	0.205	WI	0.169
KS	0.204	OH	0.169
NE	0.204	FL	0.168
KY	0.204	MI	0.164
WV	0.203	MD	0.163
TN	0.200	NH	0.163
AR	0.197	PA	0.162
AZ	0.195	VT	0.160
GA	0.192	ME	0.159
DE	0.192	CT	0.154
MO	0.192	CA	0.153
IA	0.191	RI	0.152
NV	0.191	NY	0.149
IN	0.190	NJ	0.149
TX	0.186	MA	0.147

is 0.0039. Given the small reported parameter estimate for ln organic pasture (0.007), the increase in the p-value from 0.034 to 0.055 is not surprising. Thus, it can be argued that the bootstrapped standard error, although slightly larger, still maintains marginal statistical significance at the 0.05 level. Given the small difference between the original standard error and the bootstrapped standard error, it may be reasonable to indicate a suggestive relationship between ln organic pasture and GHG emissions.

In sum, the bootstrapped estimations suggest that the results reported in Table 2 do not appear to be affected by influential observations and, as a result, provide a relatively reliable and accurate assessment of our hypothesized relationships.

5. Spatial analysis

The parameter estimates reported in column (4) of Table 2 can be used along with point estimates for relevant variables to produce GHG emissions for individual states. The following equation is derived using only statistically significant coefficient estimates for the key variables, namely the variables related to farming and organic agriculture.

$$\begin{aligned} \ln \mathrm{GHG}_{it} &= 0.131 \ln \mathrm{FARMLAND}_{it} - 0.059 \ln \mathrm{ORGCROP}_{it} \\ &\quad - 0.007 \ln \mathrm{ORGPAST}_{it} \end{aligned} \tag{5}$$

Eq. (5) basically shows that the farmland variable contributes positively the most to GHG emissions, followed by the organic cropland and organic pasture variables, respectively, which contribute negatively to GHG emissions. Mean values for each of the relevant variables are then substituted into these equations to derive point estimates of the state-level environmental impact. These estimates are then scaled using point estimates of the population variable that are weighted using the parameter estimate reported in Table 2 (i.e. 0.541). This process essentially yields state-level estimates of per capita GHG emissions arising from agriculture.

Table 4 provides estimates of GHG emissions for individual states in the contiguous United States. For instance, Wyoming has the largest GHG emissions (0.226), which are 1.5 times greater than those in Massachusetts (MA), where GHG emissions are the lowest (0.147). By utilizing a user-written Stata *spmap* command, we can visually represent the spatial distribution of these emissions. The resulting map uses different colors to indicate four quantiles for environmental emissions, with red representing the high-emissions class and dark blue representing the low-emissions class.

Fig. 2 shows the spatial distribution of agricultural GHG emissions, revealing one high-emissions cluster and a small high-emissions group. The high-emissions cluster is located in the center of the country and is comprised of seven states, namely Kansas (KS), Montana (MT), North Dakota (ND), Nebraska (NE), Oklahoma (OK), South Dakota (SD), and Wyoming (WY), and extending further south to New Mexico (NM). The high-emissions group is located in the southeast and is comprised of four states, namely Alabama (AL), Mississippi (MS), Louisiana (LA), and South Carolina (SC).

The larger cluster is located in an area generally known as the "Great Plains", which is largely dependent on agricultural activities such as livestock grazing and the production of alfalfa, barley, canola, corn, cotton, sorghum, soybeans, and wheat (Wishart, 2004). Table 5 shows that for all the listed states, a large proportion of their GDP comes from agriculture. Farming in SD is the largest, representing 5.94% of GDP followed by ND (5.59%) and NE (4.29%). Farming in MT ranks sixth representing 2.37% of GDP followed by KS (2.22%). The remaining states, OK, NM, and WY, rank 11th, 12th, and 15th with farming representing 1.17%, 1.12%, and 1.11% of GDP, respectively. It

Table 5
Mean farming (% GDP) and organic cropland (% farmland), 1997–2010.

State	Organic	Rank	Farming	Rank	State	Organic	Rank	Farming	Rank
VT	3.130	1	0.946	17	FL	0.137	25	0.571	26
ME	1.496	2	0.528	28	SD	0.133	26	5.939	1
NY	0.933	3	0.142	43	NV	0.110	27	0.162	42
CA	0.914	4	0.870	20	WY	0.109	28	1.111	15
ID	0.710	5	3.520	4	VA	0.096	29	0.243	39
WI	0.652	6	1.111	14	IL	0.089	30	0.507	30
NH	0.432	7	0.136	44	AR	0.082	31	2.085	8
MI	0.427	8	0.438	32	KS	0.077	32	2.218	7
MN	0.396	9	1.311	10	MO	0.074	33	0.819	21
UT	0.368	10	0.420	34	TX	0.061	34	0.549	27
ND	0.332	11	5.585	2	AZ	0.057	35	0.517	29
MA	0.322	12	0.063	48	NM	0.044	36	1.124	12
WA	0.316	13	0.911	18	IN	0.039	37	0.755	23
NJ	0.306	14	0.103	46	NC	0.037	38	0.788	22
OR	0.305	15	1.119	13	OK	0.023	39	1.171	11
PA	0.271	16	0.362	37	DE	0.023	40	0.488	31
OH	0.244	17	0.418	35	WV	0.020	41	0.170	41
CO	0.223	18	0.669	24	KY	0.017	42	1.000	16
IA	0.216	19	3.442	5	GA	0.012	43	0.602	25
MT	0.213	20	2.367	6	TN	0.012	44	0.353	38
RI	0.203	21	0.065	47	LA	0.005	45	0.397	36
MD	0.196	22	0.210	40	MS	0.004	46	1.411	9
NE	0.159	23	4.287	3	SC	0.003	47	0.433	33
CT	0.143	24	0.114	45	AL	0.003	48	0.895	19

is worth noting that although the economies of the listed “Great Plains” states depend on farming, only a small proportion of their farmland is dedicated to organic agriculture. Table 5 shows that with the exception of ND, which ranks 11th in the country with 0.33% of its farmland dedicated to organic agriculture, the rankings of the remaining states range between 20th and 0.21% of farmland (MT) and 39th and 0.02% of farmland (OK).

A notable observation about the smaller high-emissions group is that organic agriculture is virtually absent. For instance, Table 5 shows that MS ranks 9th for farming (1.41% of GDP) but 46th for organic agriculture (0.004% of farmland). The remaining three states, namely AL, SC, and LA rank 19th, 33rd, and 36th in farming and 48th, 47th, and 45th in organic agriculture, respectively.

Fig. 2 also displays a group of low-emissions states, with California (CA) being the largest contributor to this category where agriculture contributes 0.87% to GDP and organic farming represents 0.91% of total farmland. There is also a cluster of 11 low-emissions states in the northeastern region, extending to Michigan (MI) in the north and Maryland (MD) in the south. Farming activities contribute significantly less to the GDP of these states when compared to the high-emissions cluster. The highest contribution to GDP comes from Vermont (VT) at 0.95% of its GDP and the lowest is in Massachusetts (MA) at 0.063%. However, organic agriculture is substantially larger in most states, with rates ranging between 3.13% in VT and 0.14% in CT.

6. Discussion and conclusions

This paper makes use of U.S. state-level data over the 1997–2010 period to estimate and map emissions arising from agricultural activities while accounting for the role that organic agriculture can play in mitigating GHG emissions. The analysis presented in this paper is both broad and deep in its approach. On one hand, it covers a large scope by using panel state-level data to estimate and map emissions arising from agricultural activities across the United States. This allows for a comprehensive view of the spatial distribution of agricultural greenhouse gas emissions across the country. On the other hand, the analysis goes in-depth by accounting for the role that organic agriculture plays in mitigating GHG emissions.

The study finds that a one percent increase in total farmland results in a 0.13 percent increase in GHG emissions, while a one percent increase in organic cropland and pasture leads to a decrease in emissions by about 0.06 percent and 0.007 percent, respectively. These results align with those reported in Squalli and Adamkiewicz (2018) and are used to derive estimates for agricultural emissions for individual states, accounting for the effect of organic farming and pasture. The spatial distribution of these estimates yields the following insights:

1. **The spatial distribution of agricultural GHG emissions in the United States is uneven**: High-emissions states are concentrated in the Great Plains extending south to NM and the southeastern area of the United States. Meanwhile, low-emissions states are in California and the northeastern region extending to MI in the north and MD in the south.
2. **Agriculture is a significant contributor to GDP within the high-emissions states but organic agriculture represents only a small proportion of total farmland**: The contribution of agriculture to GDP in high-emissions Great Plains states ranges from 1.11% to 5.94%, while organic agriculture as a share of total farmland ranges from 0.02% to 0.33%. In the southeastern states, the contribution of agriculture to GDP ranges from 0.39% to 1.41%, and organic agriculture ranges from 0.003% to 0.005%.
3. **Agriculture has a substantially lower contribution to GDP within low-emissions states but organic agriculture represents a large proportion of total farmland**: The contribution of agriculture to GDP ranges from 0.063% to 0.95%, while organic farming as a share of total farmland ranges from 0.14% to 3.13%.

The insights derived from the spatial analysis indicate that reducing GHG emissions effectively may necessitate creating and implementing policies and initiatives tailored to specific regions rather than relying on general recommendations. This means that policies crafted to address the unique characteristics of the agricultural sectors in the Great Plains and southeastern regions could be more successful in promoting sustainable agricultural practices and reducing GHG emissions. Thus, low-emissions states should be explored as potential examples of sustainable agricultural practices that could be adopted in other parts of the country.

The findings of this study have significant policy implications. The estimated ecological elasticities related to organic farming and pasture along with the spatial distribution of GHG emissions across the United States offer empirical evidence of the potential for organic farming to mitigate GHG emissions. Policymakers can use these results to develop appropriate policies to encourage the transition from conventional to organic farming practices and to scale up organic farming. The scaling up of organic agriculture, especially in farming-dependent states, has the potential to significantly contribute to the mitigation of GHG emissions, thereby helping the United States and the world meet their emission reduction targets.

Beyond mitigating GHG emissions, scaling up organic agriculture would have many potential benefits. For instance, it could help the growth of rural communities, which represent major sources of organic products. Supporting the growth of organic farms in such communities can provide well-needed economic opportunities and increase the availability of healthier and nutritious food options especially in areas with limited access. Upscaling organic farming can also be particularly beneficial in developing countries where farmers typically depend on external inputs, such as synthetic fertilizers and pesticides. Organic farming reduces dependency on such inputs and can contribute to a better diversification of the farmers' income streams and increased resilience to market fluctuations.

Of course, scaling up organic agriculture is not an easy task. Organic farming often requires more labor and more expensive inputs than conventional farming. While this can make organic farming financially unattractive in the short term, improved soil health, reduced pollution, and the scaling of organic farming could help offset or reduce these costs over time. Another challenge is the need to educate farmers, consumers, and policymakers about the benefits of organic agriculture. Many farmers and consumers, especially in developing countries, may not be familiar with organic farming techniques and their environmental, health, and economic benefits, and may need education, training, and support to make the transition. Finally, policymakers should incorporate scientific advances in their work in order to ensure that their policies are based on concrete evidence and are not influenced by personal beliefs and political biases.

The paper faces some limitations, which should be addressed in future research. First, although the data we use in this study account for carbon sequestration from changes in land use and forestry management, they do not capture sequestered soil carbon from organic agricultural. As a result, the estimates produced by this study may understate the true environmental benefits of organic farming. Indeed, GHG estimates are based on inventories and actual sources and sinks may vary since we do not have a complete understanding of these processes. Second and as highlighted by Squalli and Adamkiewicz (2018), WRI's use of SIT default data, which ignores potentially more accurate activity data provided by individual states, raises accuracy concerns. Third, the study does not account for the effect of livestock on GHG emissions, which could be significant especially in the Great Plains. For instance, cows feeding on pasture produce more methane than those feeding on grain. These differences are clearly not directly captured by our data. Fourth, our data do not control for the ecologically-sound processes that are typically used to manage the land and that are known to play a significant role in reducing the carbon footprint of agriculture. Finally, while GHG emissions are an important factor to consider, there are other environmental elements that can be affected by farming activities, such as water quality, soil health, biodiversity, and ecosystem function. Thus, this analysis only provides a partial understanding of the environmental impact of agricultural practices.

CRediT authorship contribution statement

Jay Squalli: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – original draft, Writing – review & editing. **Gary Adamkiewicz:** Conceptualization, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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