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The potential cost of regulation of methane and nitrous oxide emissions in U.S. agriculture

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Abstract

Background: Most studies on the environmental impacts of agriculture have attempted to measure environmental impacts but have not assessed the ability of the sector to reduce or mitigate such impacts. Only a few studies have examined greenhouse gas emissions from the sector. This paper assesses the ability of states in the U.S. to reduce agricultural emissions of methane and nitrous oxide, two major greenhouse gases (GHGs) with important global warming potential.

Methods: The analysis evaluates Färe's PAC (pollution abatement cost) for each state and year, a measure of the potential opportunity costs of subjecting the sector to GHG emissions regulation. We use both hyperbolic and directional distance functions to specify agricultural technology with good and bad outputs.

Results and conclusions: We find that such regulations might reduce output by an average of about 2%, although the results for individual states vary quite widely.

Keywords: Pollution abatement costs, Methane, Nitrous oxide, U.S. agriculture

JEL Classifiactions: Q51, Q54, C61

Background

The Intergovernmental Panel on Climate Change (IPCC 2014) estimated that as of 2010, agriculture accounted for 24% global anthropogenic greenhouse gas (GHG) emissions, versus 21% from industry and 14% from transportation. In the U.S. in 2013, agriculture accounted for approximately 9% of GHG emissions. Since 1990, agricultural emissions had increased by approximately 13%, the main driver being the growth in combined methane (17.5%) and nitrous oxide emissions (10.4%).[1] It is worth noting that the global warming potential of methane and nitrous oxide are respectively 28–36 and 265–298 times that of carbon dioxide. Methane has, on average, a 10 year and nitrous oxide a 100 year lifespan in the atmosphere.[2] Nitrous oxide is also one of the leading ozone depleting substances. These environmental impacts have made the agricultural sector a subject of several federal and state regulatory efforts in the U.S.: the Clean Air Act of 1970, the Global Warming Reduction Act of 2006, the Safe Climate Act of 2006, the Climate Stewardship and Innovation Act of 2005, the Clean Power Plan of 2015, and the Regional Greenhouse Gas Initiatives, among others. The 2010 EPA proposals, Prevention of Significant

[1] https://cfpub.epa.gov/ghgdata/inventoryexplorer/#iagriculture/entiresector/allgas/gas/all. Accessed July 19, 2021.

[2] https://www.epa.gov/ghgemissions/understanding-global-warming-potentials. Accessed July 19, 2021.

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Deterioration and Title V Greenhouse Gas Tailoring Rule, prompted stationary sources, agricultural production units included, to obtain permits if their actual emissions or potential to emit go beyond certain established thresholds.[3] A recent proposal that reflects these concerns is The Energy and Innovation and Carbon Dividend Act introduced in the U.S. Congress in 2018 and reintroduced in 2019 and 2021 that proposes a carbon fee at the source and dividends redistributed across the population. The unique perspective of the present research is relevant to these proposals, because we provide estimate of the opportunity cost of compliance with potential regulation.

Methods

This study examines the efficiency of individual U.S. states with respect to their production of livestock, crops and greenhouse gases (GHGs). To measure environmental performance accounting for undesirable outputs in a production process, a number of economic tools have been employed. Both non-parametric data envelopment analysis (DEA), Reinhard (1999), and stochastic as well as deterministic parametric distance functions (Rezek and Perrin 2004; Serra et al. 2011) have been used to represent feasible technologies and thereby assess the performance of decision-making units (DMUs). We use non-parametric data envelopment techniques (hyperbolic and directional output distance functions) to identify the feasible technology and measure the potential decrease in GHG emissions of the individual states. We postulate a state-level agricultural production technology, T, that transforms inputs $x \in \mathbb{R}_+^N$ into desirable outputs $y \in \mathbb{R}_+^M$ and weakly disposable undesirable outputs $b \in \mathbb{R}_+^J$ such that $T = \{(x, y, b) : x\, can\, produce(y, b)\}$. Alternatively, the technology can be characterized by the compact output set as $P^W(x) = \{(y, b) : (x, y, b) \in T\}$, satisfying the axioms of null jointness in desirable and undesirable outputs, weak disposability in undesirable outputs and strong disposability in desirable outputs.

Hyperbolic efficiency

The enhanced hyperbolic productive efficiency measure used here follows Färe et al. (1989). It measures for each individual decision-making unit (DMU—states in our case) the potential for equi-proportional expansion of desirable outputs and contraction of undesirable outputs as well as inputs, given the feasible production technology that has been revealed by the set of 48 states. In

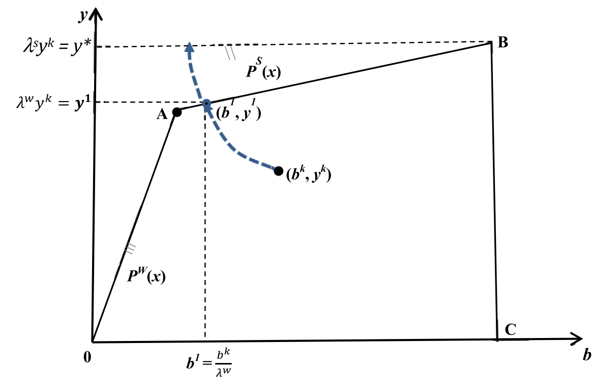

Fig. 1 Hyperbolic efficiency measure

Fig. 1 the vertices A and B represent combinations of bad and good output achieved by two DMUs on the frontier, while (b^k, y^k) represents that for DMU k, whose efficiency we examine in this figure. Assuming weak disposability of environmentally undesirable outputs, the hyperbolic output efficiency measure for state k, representing the potential for simultaneous and equi-proportional expansion in desirable outputs and contraction in undesirable outputs and inputs is defined as follows:

$$HE^w\left(\boldsymbol{x}^k, \boldsymbol{y}^k, \boldsymbol{b}^k\right) = Max\{(\lambda : \lambda \boldsymbol{y}^k, \lambda^{-1}\boldsymbol{b}, \lambda^{-1}\boldsymbol{x}^k) \in P^w(\boldsymbol{x})\} \quad (1)$$

If instead of weak disposability in undesirable outputs we were to impose strong disposability (i.e., it does not cost anything to dispose of these outputs), the measure would be

$$HE^s\left(\boldsymbol{x}^k, \boldsymbol{y}^k, \boldsymbol{b}^k\right) = Max\{(\lambda : \lambda \boldsymbol{y}^k, \lambda^{-1}\boldsymbol{b}, \lambda^{-1}\boldsymbol{x}^k) \in P^s(\boldsymbol{x})\} \quad (2)$$

Figure 1 illustrates these two measures for DMU k, where the feasible weakly disposable technology is represented by the convex solid projection curve shown, and the feasible *strongly* disposable technology is illustrated by the continuing dashed projection to the level of maximum producible output y^*. When b is strongly disposable, the DMU can produce at the maximum y^* whatever level of b, then simply dispose of all the b, providing an effective output combination on the vertical axis at $\lambda^s y^k = y^*$. A DMU is efficient if it is on the frontier, and in this case, $HE\left(\boldsymbol{x}^k, \boldsymbol{y}^k, \boldsymbol{b}^k\right) = 1$. It is inefficient when $HE\left(\boldsymbol{x}^k, \boldsymbol{y}^k, \boldsymbol{b}^k\right) > 1$. In this study we use Data Envelopment Analysis (DEA) to calculate these measures. The programming algorithms are shown in Appendix 1.

PAC—a measure of pollution abatement cost

Färe et al. (1989) proposed, in the context of hyperbolic efficiency, that the ratio of the efficiency measures under

[3] At least 75,000 tons per year (tpy) of carbon dioxide equivalent (CO2e) and an increase in emissions of at least one non-GHG pollutant as of January 2, 2011 on a first step. And at least 100,000 tpy CO2e as of July 11, 2011 as second step. Source emissions below 50,000 tpy CO2e, and no modification resulting in net GHG increases of less than 50,000 tpy CO2e, would be subject to PSD or title V permitting as of April 30, 2016.

strong disposability (λ^s) and weak disposability (λ^w) is a "measure of the regulatory impact, conceived in terms of reduced productivity due to a forced departure from strong disposability of undesirable outputs." or of the cost to that DMU of being unable to freely dispose of the bad. Färe et al. (2007) subsequently named this ratio PAC (pollution abatement cost), and it has been used in a number of applications (Färe et al. 2016a, b; Liu and Sumaila 2010).

The logic of PAC as a measure of pollution abatement cost is as follows. Consider the projection of DMU k from (b^k, y^k) to the weakly disposable technology frontier at ($b^k/\lambda^w = b^1$, $\lambda^w y^k = y^1$), as indicated in Fig. 1. If b were freely disposable, the now efficient DMU could increase y to the point of maximum desirable output, y^*, then dispose of all the b. But y^* is equal to $\lambda^s y^k$, the point on the frontier to which we have projected the DMU using HE^s under strong disposability. The ratio λ^s / λ^w is thus equal to the ratio y^*/y^1, the ratio of the amount of good output the DMU could produce under free disposability, relative to the good output at the efficient point on the weakly disposable frontier to which it is hyperbolically projected.

Our reservation with respect to this interpretation is that it is measured from the point on the weak disposability frontier to which we project the state. The projection path in general is purely arbitrary—it could be projected along any number of other paths, as we suggest in the next section, rather than a hyperbolic projection. There is no particular reason for us to believe that if the DMU were to become technically efficient, it would perform at the projected point, and it is highly unlikely that any conceivable regulatory policy would cause the agricultural DMU to move to that particular projection point. Still, there is intuitive appeal and precedent for interpreting the ratio as potential regulatory impact such that a binding regulation on DMU k results in $\lambda^s/\lambda^w > 1$ and in $\lambda^s/\lambda^w = 1$ in the absence of regulation (or in production of y^1 versus the y^* that would be produced in the absence of regulation, where $y^*/y^1 = \lambda^s/\lambda^w$). Rather than to follow Färe by defining PAC as the ratio λ^s/λ^w, we define PAC as the difference, $\lambda^s - \lambda^w$, which we then multiply by the dollar-valued y^k to measure the dollar value of the PAC. This allows adjustment for the size of the agricultural production activity in each state. Accordingly, a measure of the cost of regulation, or the cost of being unable to dispose of the bad output freely, can be approximated by Eq. (3). We interpret this as the value of the hyperbolic pollution abatement cost (PAC) in this study:

$$Value\ of\ PAC_{HE}^{k} = \boldsymbol{y}_k * \left[HE^s\left(\boldsymbol{y}^k, \boldsymbol{b}^k, \boldsymbol{x}^k\right) - HE^w\left(\boldsymbol{x}^k, \boldsymbol{y}^k, \boldsymbol{b}^k\right)\right] \tag{3}$$

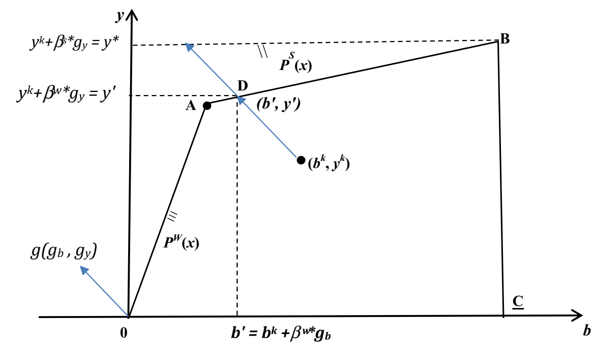

Fig. 2 Directional distance function

A directional output efficiency measure

Generalization of the output distance function has led to consideration of the directional output distance function to measure efficiency, which is suitable and convenient for gauging performance of a production process with both desirable and undesirable outputs. Performance measures associated with the directional distance function include a number of nonparametric and nonstochastic indexes (Chambers et al. 1996; Oh and Heshmati 2011) as well as parametric, deterministic and stochastic, approaches (Silva et al. 2019; Badau et al. 2016; Summary and Weber 2012; Färe et al 2007). In this study we use Data Envelopment Analysis (DEA) to obtain the directional output distance function to assess efficiency in the presence of GHG emissions conceptualized as a bad output.

The directional output distance function also measures efficiency by projecting individual DMU observations to the technology frontier, but along a chosen ray from its observed point rather than along a hyperbolic path, as illustrated in Fig. 2 and described next.[4] This efficiency measure is defined as the maximum feasible multiple, β, of additional output units and subtraction of input units given a directional vector $\boldsymbol{g} = \left(\boldsymbol{g_y}, \boldsymbol{g_x}\right)$, which identifies the units of y and x, respectively:

$$\vec{D}^k\left(\boldsymbol{y}^k, \boldsymbol{x}^k; g_y, g_x\right) = Sup\left[\beta : \left(\boldsymbol{y}^k + \beta \boldsymbol{g_y}, \boldsymbol{x}^k - \beta \boldsymbol{g_x}\right) \in P(\boldsymbol{x})\right] \tag{4}$$

which is referred to as a directional distance function.[5] In the context of a joint production process of undesirable and desirable outputs, an environmental directional distance function ($\vec{\boldsymbol{D}}_{\boldsymbol{E}}^{\boldsymbol{k}}$) can be defined similarly as follows:

[4] Färe et al (2016a, b) shows that the directional distance function is a linear approximation to the hyperbolic distance function.

[5] The directional distance function satisfies the translation property, homogeneity of degree -1 in $\left(\boldsymbol{g_x}, \boldsymbol{g_y}\right)$, monotonicity, and concavity.

$$\vec{D}_E^k\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right) = Sup\left[\beta : \left(\boldsymbol{y}^k+\beta\boldsymbol{g_y},\boldsymbol{b}^k-\beta\boldsymbol{g_b},\boldsymbol{x}^k-\beta\boldsymbol{g_x}\right)\in P(\boldsymbol{x})\right] \tag{5}$$

where $\boldsymbol{g}=\left(\boldsymbol{g_y},-\boldsymbol{g_b},-\boldsymbol{g_x}\right)$ is a vector determining the direction in which the desirable output is expanded and the inputs and undesirable outputs are contracted. The directional distance function also differs from the hyperbolic distance function by its additive, rather than multiplicative, scaling. $\vec{D}_E^k\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right)$ as defined in Eq. 5 can be computed by solving the linear programming problem in Appendix 1. A DMU is said efficient in the $\left(\boldsymbol{g_x},\boldsymbol{g_y},\boldsymbol{g_b}\right)$ direction if it is on the boundary, *i.e.*, exhibits a $\vec{D}_E^k\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right)=0$. It is inefficient when $\vec{D}_E^k\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right)>0$. As with the hyperbolic, the directional distance can be obtained for production sets with strong disposability as follows:

$$\vec{D}_E^{Sk}\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right) = Sup\left[\beta : \left(\boldsymbol{y}^k+\beta\boldsymbol{g_y},\boldsymbol{b}^k-\beta\boldsymbol{g_b},\boldsymbol{x}^k-\beta\boldsymbol{g_x}\right)\in P^S(\boldsymbol{x})\right] \tag{6}$$

where S indicates a strongly disposable production set.

The choice of the directional vector is somewhat arbitrary. If (g_x,g_y,g_b) is set to $(0,1,-1)$ the directional distance function projects the observation by increasing good output by one unit and decreasing bad output by one unit while holding inputs constant. For consistency with the original Farrell efficiency measures and the Shephard distance functions, the observed input and output mix has been used as the directional vector.[6] This output directional distance function is depicted in Fig. 2, where the directional vector $(g_y,-g_b)$ shown in the left quadrant is added to the observed vector (y^k,b^k) so the *k-th* observation is projected along the assigned direction to point $D=(y+\beta^*g_y,b-\beta^*g_b)$ on the boundary of the weakly-disposable output set, $P^w(x)$.

Analogous to the case of the hyperbolic distance function, a measure of pollution abatement cost (PAC) for DMU k resulting from a directional distance function is computed as $\beta^s-\beta^w$ with the value of the directional pollution abatement cost (PAC) as:

$$Value\ of\ PAC_{DDF}^k = y_k*\left[(\vec{D}_E^S\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right) - \vec{D}_E^W\left(\boldsymbol{y}^k,\boldsymbol{b}^k,\boldsymbol{x}^k;\boldsymbol{g_y},\boldsymbol{g_b},\boldsymbol{g_x}\right)\right] \tag{7}$$

where S and W refer to directional distances with strong and weak disposability respectively.

Data

In this study we examine the potential cost to the state-level agricultural sector in the U.S. of regulating methane and nitrous oxide emissions, using data from 1992 to 2003.[7] The agricultural outputs are multilateral indexes of crop production and livestock production (indexed to Alabama, 1996 equal to 1.0), while the agricultural inputs are similar multilateral indexes of capital, land, labor, energy, chemical, pesticides and fertilizers. Details and documentation on methods to compute these indexes can be found in the USDA ERS Agricultural Productivity website.[8] We also used the implicit quantity of livestock and crop from the same source to determine a dollar value of a potential emissions regulation. The undesirable output from agriculture is from the Environmental Protection Agency (EPA), reported in their website.[9]. We converted the EPA estimates of methane and nitrous oxide emissions into CO2 equivalents and then indexed that quantity to Alabama 1996 = 1 for compatibility with the USDA ERS indexes of agricultural inputs and desirable outputs. Table 1 shows descriptive statistics for the data.

Results and discussion

In Table 2 we compare annual average values of PAC using hyperbolic projections versus directional distance function projections, along with the average values of efficiencies under strong versus weak disposability used to calculate these PACs. This table provides an estimate of the proportion of agricultural production that would potentially have to be sacrificed, by year, to reduce these gases, or the average opportunity cost of regulating these gases by year. Looking first at the average value (last line), we see that the average PAC is 0.020 using the hyperbolic projection versus 0.016 using the directional distance function projection. The average strong disposability and weak disposability scores under hyperbolic projection are 1.115 and 1.095, respectively. Referring to Fig. 1, this indicates that on average the long arc to the

[6] Alternatively, Zofio et al. (2010) propose the use of market prices as directional vector to measure economic inefficiency in terms of foregone profits.

[7] The USDA ERS calculation of input and output indexes by states for the agricultural sector was discontinued in 2004.

[8] See Ref. [15].

[9] United States Environmental Protection Agency (US EPA), 2010. Inventory of U.S. greenhouse gas emissions and sinks: 1990–2008. Washington D.C. https://www3.epa.gov/climatechange/Downloads/ghgemissions/508_Complete_GHG_1990_2008.pdf. Accessed on November 10, 2016. This url has been discontinued, but similar information can be obtained at https://cfpub.epa.gov/ghgdata/inventoryexplorer/#iagriculture/entiresector/allgas/gas/all.

Table 1 Data descriptive statistics: yearly state-level data on agricultural outputs and inputs for U.S. 48 States, 1990–2004

Variables*	Mean	Std Dev	Minimum	Maximum
y1 Crops	2.9426	3.4521	0.0327	22.9963
y2 Livestock	0.8655	0.7953	0.004	3.7274
b3 Methane	3.0913	5.584	0.0051	30.3838
b4 Nitrous Oxide	2.4751	2.4652	0.0093	12.7775
x1 Capital	1.5736	1.3427	0.0208	6.1439
x2 Labor	1.9615	2.1647	0.0118	13.6648
x3 Land	1.9396	1.7162	0.0242	11.2267
x4 Energy	1.7249	1.594	0.0153	8.3163
x5 Chemicals	1.9772	2.0939	0.0081	9.8501
x6 Pesticides	1.8768	1.9894	0.0045	11.5596
x7 Fertilizer	2.0512	2.2991	0.0101	12.7621

*All indexes with respect to Alabama in 1966, 1996 dollars

Source: ERS: https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/ Accessed on November 10, 2016 and EPA: https://www3.epa.gov/climatechange/Downloads/ghgemissions/508_Complete_GHG_1990_2008.pdf. Accessed on November 10, 2016. This url has been discontinued but information can be found at https://cfpub.epa.gov/ghgdata/inventoryexplorer/#iagriculture/entiresector/allgas/gas/all

dashed line represents an 11.5% increase in good output y and an 11.5% decrease in bad output b. The difference between these two, 1.115–1.095 = 0.020, suggests as we have argued above that a plausible average measure of PAC, the pollution abatement cost, is 2%. The averages of the two directional distance function measures are 0.099 and 0.083, reflecting alternatively a 9.9% or 8.3% increase in y and reduction in b, with the difference of 0.099–0.083 = 0.016 again interpreted as the average abatement cost. These results thus indicate that the average potential regulatory burden would be about 1.6–2.0% of the value of agricultural output.

The results indicate a strong increase in PACs from 1992 to 1995 (from 0.9 to 3.7%), settling back to quite constant levels around 1.7% to 2.1% from 1996 to 2003. This pattern holds for both the hyperbolic and the directional distance function specifications of technology. The results translated into dollar values are shown in Table 3. The cumulative costs over the period are in the vicinity of $28–33 billion dollars (1996 dollars), and range from about $1 billion in 1992 to $4 billion in 1995.

Broken out by crops versus livestock in Table 4, we observe quite similar patterns through time for the livestock and crop sectors, reflecting the previously-mentioned increase from 1992 to 1995 before settling to more year-to-year stability afterward. The pollution abatement costs fluctuate more widely for livestock products than for crops.

Table 2 Average agriculture PACs (Pollution Abatement Costs) for U.S. states, using hyperbolic and directional distance function projections

	Using the hyperbolic projection			Using the directional distance function projection		
	Disposability		PAC	Disposability		PAC
	Strong	Weak		Strong	Weak	
	Eq. (2)	Eq. (1)	Eq. (3)	Eq. (6)	Eq. (5)	Eq. (7)
1992	1.051	1.042	0.009	0.047	0.039	0.008
1993	1.067	1.057	0.010	0.061	0.052	0.009
1994	1.108	1.081	0.027	0.095	0.072	0.023
1995	1.173	1.136	0.037	0.147	0.117	0.030
1996	1.113	1.094	0.019	0.097	0.081	0.016
1997	1.117	1.096	0.021	0.101	0.084	0.018
1998	1.109	1.089	0.019	0.095	0.078	0.017
1999	1.123	1.105	0.018	0.106	0.091	0.015
2000	1.128	1.111	0.017	0.107	0.094	0.014
2001	1.109	1.089	0.019	0.095	0.078	0.017
2002	1.138	1.120	0.018	0.118	0.104	0.015
2003	1.109	1.089	0.019	0.095	0.078	0.017
Average	1.115	1.095	0.020	0.099	0.083	0.016

Table 3 Yearly value of PAC's for U.S. agriculture, 1992–2003, in thousands of 1996 dollars

Years	Hyperbolic	Directional distance function
1992	1,055,286	952,172
1993	1,772,681	1,558,840
1994	2,801,434	2,389,808
1995	4,174,007	3,379,392
1996	2,982,051	2,570,677
1997	2,909,866	2,491,566
1998	2,627,978	2,189,271
1999	2,404,276	2,087,126
2000	3,408,032	2,829,113
2001	3,159,689	2,710,648
2002	2,820,788	2,394,933
2003	3,018,292	2,668,993
Sum	33,134,381	28,222,545

Table 4 Yearly Value of PACs for Livestock and Crop Production in U.S. Agriculture, 1992–2006, in thousands of 1996 dollars

Years	Livestock production		Crop production	
	Hyperbolic	Directional distance function	Hyperbolic	Directional distance function
1992	451,038.29	406,989.87	604,247.65	545,182.80
1993	868,546.80	755,059.09	904,134.10	803,781.80
1994	1,503,043.88	1,261,997.64	1,298,389.77	1,127,811.12
1995	2,315,960.49	1,834,523.13	1,858,046.94	1,544,868.99
1996	1,371,197.23	1,162,721.53	1,610,853.82	1,407,956.43
1997	1,487,465.47	1,249,765.78	1,422,400.90	1,241,801.14
1998	1,349,604.82	1,095,302.04	1,278,373.52	1,093,969.10
1999	1,281,805.01	1,089,358.54	1,122,471.34	997,767.78
2000	1,750,778.28	1,390,320.24	1,657,253.93	1,438,792.79
2001	1,681,820.97	1,421,724.78	1,477,867.75	1,288,923.87
2002	1,498,988.88	1,238,842.29	1,321,799.46	1,156,090.90
2003	1,585,747.78	1,396,574.55	1,432,543.85	1,272,418.90
Sum	17,145,997.90	14,303,179.48	15,988,383.03	13,919,365.61

Table 5 reports PACs for individual states.[10] Whereas the overall average hyperbolic PAC is 0.020 (2% of output), averages for individual states range from 0.0 for eight states to 0.125 for Delaware. The directional distance function results are similar, measuring an overall average PAC of 0.016, while averages for individual states range from 0.00 to 0.115 for Delaware. States with high PACs tend to be those with high ratios of livestock to crop production such as Alabama, Georgia, Maryland, South Carolina and Delaware. These states would potentially have to sacrifice from 7 to 12.5% of their agricultural output if regulation were imposed to reduce these gasses. Their potential opportunity costs are thus quite substantial. But in general, our estimates of PAC costs represent a small proportion of the value of U.S. agricultural production (around 2%), given the size of the agricultural sector in these states. The average value of PAC per state allows adjustment to the size of agricultural activity in each state and it is shown in Appendix Table 6. The states with higher values sacrificed during the 1992–2003 period are Georgia, Alabama, Minnesota, Michigan, North Carolina and South Carolina. For the U.S. this amounts to a cost of $28–$33 billion (1996 dollars) during this period.

What about the eight states with an average PAC of 0.0? Nominally, a PAC of zero indicates that if the state could operate with full efficiency on the frontier to which it was projected that year (only New Hampshire achieved a point actually on the frontier in every one of the 12 years), no output need be sacrificed due to a forced departure from free disposability of the polluting outputs. Geometrically, this implies that the weakly disposable frontier and the strongly disposable frontier coincide at the point to which the state is projected. Referencing Fig. 1, the frontiers coincide at B, so the distance of the projection is the same to the two frontiers, and thus $\lambda^s - \lambda^w = 0$.

The average state-level pollution abatement costs, expressed in 1996 dollars (Table 6), we obtain by multiplying the PAC (measured in fraction of output) times the value of output. Results are similar in pattern across states to the PACs themselves. However, the rankings of states by total cost of pollution abatement can be quite different from rankings by PAC, simply because of differences in the sizes of the agricultural sectors.

Conclusions

This study has estimated the potential regulatory cost, at the level of states in the U.S., if agricultural methane and nitrous oxide had been regulated, for each year from 1992 to 2003. We obtain these measures using established non-parametric DEA methods of analyzing and interpreting production sets for an industry that produces undesirable, as well as desirable outputs. Our state-level agricultural input and output data are from ERS, USDA, while state-level data on agricultural emissions of methane and nitrous oxide were obtained from EPA.

[10] This table also reports the hyperbolic and the directional measures for individual states. For Colorado for example, an average hyperbolic measure of 1.075 indicates that under strong disposability this state could increase output by 7.5% and decrease input use by the same percentage relative to the best performance state. The directional distance for Colorado indicates that the state could, on average, increase output by 7.2% and decrease inputs by 7.2% relative to the most efficient state.

Table 5 Average hyperbolic and directional distance function efficiency measures with strong and weak disposability and their PACS, 1992–2003

States	Hyperbolic			DDF		
	λ^s	λ^w	$\lambda^s - \lambda^w$	β^s	β^w	$\beta^s - \beta^w$
AL	1.4748	1.4034	0.0714	0.3572	0.3176	0.0397
AR	1.0072	1.0000	0.0072	0.0069	0.0000	0.0069
AZ	1.0133	1.0075	0.0058	0.0128	0.0072	0.0056
CA	1.0030	1.0030	0.0000	0.0030	0.0030	0.0000
CO	1.0753	1.0619	0.0134	0.0717	0.0594	0.0123
CT	1.0438	1.0329	0.0109	0.0421	0.0320	0.0101
DE	1.1253	1.0000	0.1253	0.1148	0.0000	0.1148
FL	1.0011	1.0000	0.0011	0.0011	0.0000	0.0011
GA	1.1709	1.0980	0.0729	0.1560	0.0929	0.0631
IA	1.0080	1.0061	0.0019	0.0078	0.0060	0.0019
ID	1.0166	1.0164	0.0003	0.0162	0.0160	0.0003
IL	1.0109	1.0076	0.0033	0.0104	0.0072	0.0032
IN	1.0685	1.0570	0.0116	0.0646	0.0539	0.0107
KS	1.1671	1.1555	0.0116	0.1469	0.1376	0.0093
KY	1.1276	1.1268	0.0008	0.1162	0.1155	0.0007
LA	1.1063	1.1063	0.0000	0.0985	0.0985	0.0000
MA	1.0010	1.0000	0.0010	0.0010	0.0000	0.0010
MD	1.2709	1.1842	0.0866	0.2311	0.1647	0.0664
ME	1.2583	1.2104	0.0478	0.2236	0.1862	0.0373
MI	1.1644	1.1181	0.0463	0.1496	0.1105	0.0391
MN	1.1059	1.0841	0.0218	0.0974	0.0781	0.0193
MO	1.0245	1.0245	0.0000	0.0221	0.0221	0.0000
MS	1.1994	1.1994	0.0000	0.1738	0.1738	0.0000
MT	1.2568	1.2172	0.0395	0.2201	0.1889	0.0312
NC	1.0323	1.0093	0.0230	0.0313	0.0091	0.0222
ND	1.0908	1.0741	0.0167	0.0853	0.0701	0.0152
NE	1.0497	1.0476	0.0021	0.0473	0.0454	0.0020
NH	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
NJ	1.0166	1.0000	0.0166	0.0162	0.0000	0.0162
NM	1.0512	1.0320	0.0192	0.0476	0.0304	0.0173
NV	1.0031	1.0031	0.0000	0.0030	0.0030	0.0000
NY	1.0362	1.0362	0.0000	0.0340	0.0340	0.0000
OH	1.0819	1.0610	0.0209	0.0765	0.0571	0.0194
OK	1.4605	1.4580	0.0025	0.3561	0.3547	0.0014
OR	1.0446	1.0195	0.0251	0.0424	0.0191	0.0233
PA	1.1828	1.1714	0.0115	0.1621	0.1515	0.0106
RI	1.0058	1.0000	0.0058	0.0057	0.0000	0.0057
SC	1.2518	1.1584	0.0934	0.2192	0.1449	0.0744
SD	1.1173	1.1023	0.0150	0.1077	0.0942	0.0134
TN	1.1646	1.1646	0.0000	0.1482	0.1482	0.0000
TX	1.4205	1.4197	0.0008	0.3322	0.3317	0.0005
UT	1.0494	1.0469	0.0025	0.0466	0.0444	0.0023
VA	1.3086	1.3039	0.0047	0.2600	0.2566	0.0034
VT	1.0308	1.0252	0.0056	0.0290	0.0239	0.0050
WA	1.0141	1.0006	0.0135	0.0138	0.0006	0.0132
WI	1.1861	1.1740	0.0120	0.1659	0.1552	0.0108
WV	1.1587	1.0935	0.0651	0.1391	0.0868	0.0522

Table 5 (continued)

States	Hyperbolic			DDF		
	λ^s	λ^w	$\lambda^s - \lambda^w$	β^s	β^w	$\beta^s - \beta^w$
WY	1.0431	1.0421	0.0010	0.0395	0.0386	0.0009
Average	1.1146	1.0951	0.0195	0.0990	0.0827	0.0163

This is the first study to estimate, at the state level in the U.S., the pollution abatement costs for agricultural methane and nitrous oxide emissions, using the measure of potential abatement costs (PAC), as pioneered and applied by Färe and co-authors. This PAC measure is the common multiple by which the desirable outputs of a decision-making unit (DMU) could be increased measured from a point on the technology boundary to which the DMU is projected if it is not already on the boundary. This multiple represents the additional desirable output that a DMU could achieve if the undesirable output were freely disposable, compared to the output it could obtain if it could not dispose of the undesirable output without a cost. It has thus been argued to be a plausible upper bound on the potential cost of regulating the undesirable output. We use two alternative methods to project DMUs (states in our case) to the technological boundary defined by observations on all 48 states. The first method uses the enhanced hyperbolic efficiency (*HE*) trajectory, while the second method uses directional distance functions (*DDF*) for the same purpose.

Our results indicate that the average annual pollution abatement cost (PAC), across all states and years, 1992–2003, is 0.020 (2%, or around $33 billion for the period) using the hyperbolic projection, or 0.0163 (1.63% or $ 28 billion for the period) using the *DDF* projection. While these seem to be relatively small penalties, at the state level the average PACs range from 0% for eight states to 12.5% for Delaware, 9.3% for South Carolina, 8.7% for Maryland, 7.3% for Georgia, 7.1% for Alabama and 6.5% for West Virginia.

Given the data and method of analysis, it is not possible for us to directly evaluate what factors contribute to the differences in PACs across states. The analytical method presumes that any given state could achieve what any other state (or a linear combination of them) has achieved for given levels of inputs. Because of differences in agro-climatic conditions and related differences in product mix, this is not likely to be feasible. However, some of the differences in GHG efficiency are no doubt due to adoption and use of GHG mitigation technologies, environmentally friendly agricultural practices and differences in environmental regulations across states. To the extent that agriculture in a state is unable to match the level of efficiency of other states, our PAC may underestimate the pollution abatement cost.

Färe's PAC measure does not specify any particular regulatory mechanism. Because of this it only provides us with a general notion of what the regulatory cost might be. Clearly, particular regulations such as maximum permissible emissions per animal or per acre, or per unit of output, or regulations prescribing best management practices, may nudge producers toward combinations of desirable and undesirable outcomes that are postulated by the Färe PAC measure. While study of those possible outcomes are surely warranted where feasible, the PAC estimates here provide plausible measures of the relative burdens that GHG regulation might impose on the various states.

Appendices

Appendix 1: Programming problems solved

Hyperbolic efficiency measure under weak disposability defined in Eq. (1) as $HE^w\left(x^k, y^k, b^k\right) = Max\{(\lambda : \lambda y^k, \lambda^{-1}b^k, \lambda^{-1}x^k) \in P^w\left(x^k\right)\}$ computed by solving the following problem:

$$Max\ \lambda$$

Subject to

$$\sum_{k=1}^{K} z_k y_m^k \geq \lambda y_m^k \quad m = 1, \ldots, M \tag{8}$$

$$\sum_{k=1}^{K} z_k b_j^k = \lambda b_j^k \quad j = 1, \ldots, J \tag{9}$$

$$\sum_{k=1}^{K} z_k x_n^k \leq \lambda x_n^k \quad n = 1, \ldots, N \tag{10}$$

$$z_k \in R_+^K$$

where $\boldsymbol{z}^{\boldsymbol{t}}$ is an activity vector of length k used to identify the boundaries of the technology as linear combinations of observed points.

For convenience in computation, we used the following linear programming where

$$\Gamma = \lambda^2, z' = \lambda z.$$

$$Max\Gamma$$

$$\sum_{k=1}^{K} z'_k y_m^k \geq \Gamma y_m^{k'} \quad m = 1, \ldots, M \tag{11}$$

$$\sum_{k=1}^{K} z'_k b_j^k = \Gamma b_j^{k'} \quad j = 1, \ldots, J \tag{12}$$

$$\sum_{k=1}^{K} z'_k x_n^k \leq \Gamma x_n^{k'} \quad n = 1, \ldots, N \tag{13}$$

$$z'_k \in R_+^K$$

Under strong disposability $HE^S(x^k, y^k, b^k) = Max\{(\lambda : \lambda y^k, \lambda^{-1} b^k, \lambda^{-1} x^k) \in P^s(x^k)\}$ as defined in Eq. (2) is similarly solved by replacing the equal sign in the second constraint of both problems by the greater than or equal sign ($\leq$).

The environmental directional distance function ($\vec{D}_E^t$) is defined in Eq. (5) as follows:

$$\vec{D}_E^k\left(\boldsymbol{y}^k, \boldsymbol{b}^k, \boldsymbol{x}^k; \boldsymbol{g_y}, \boldsymbol{g_b}, \boldsymbol{g_x}\right) = Sup\left[\beta : \left(\boldsymbol{y}^k + \beta \boldsymbol{g_y}, \boldsymbol{b}^k - \beta \boldsymbol{g_b}, \boldsymbol{x}^k - \beta \boldsymbol{g_x}\right) \in P(x)\right]$$

where $\boldsymbol{g} = \left[\boldsymbol{g_y}, -\boldsymbol{g_b}, -\boldsymbol{g_x}\right]$ is a vector determining the direction in which the desirable output is expanded and the inputs and undesirable outputs are contracted. We compute this measure for each DMU by solving the following problem, assuming strong and weak disposability.

$max\ \beta$

Subj. to:

$$\sum_{k=1}^{K} z_k y_{km} \geq y_{km} + \beta g_y \quad m = 1, \ldots, M \tag{14}$$

$$\sum_{k=1}^{K} z_k b_{kj} = b_{kj} - \beta g_b \quad j = 1, \ldots, J \tag{15}$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_{kn} - \beta g_x \quad n = 1, \ldots, N \tag{16}$$

$$z_k \geq 0,$$

To calculate the distance for DMU k under strong disposability, the equality on the undesirable outputs in the second constraint is replaced by equal to or greater than ($\geq$).

Appendix 2: Average States' PACs

See Table 6.

Table 6 Average value of PACs for livestock and crops, 1992–2003, in thousands of 1996 dollars

State	Livestock		Crop	
	Hyperbolic $y_{iQI} * (\lambda^S - \lambda^W)$	Directional $y_{iQI} * (\beta^S - \beta^W)$	Hyperbolic $y_{iQI} * (\lambda^S - \lambda^W)$	Directional $y_{iQc} * (\beta^S - \beta^W)$
AL	2,120,574.39	1,175,449.95	683,058.76	384,524.37
AR	275,343.04	263,426.52	204,527.38	195,675.68
AZ	57,312.56	54,843.32	76,894.42	73,566.08
CA	0.00	0.00	0.00	0.00
CO	397,980.88	364,324.95	275,484.16	252,475.87
CT	29,072.68	26,935.30	29,003.16	27,032.95
DE	931,883.08	853,922.22	274,476.29	251,990.61
FL	16,187.26	16,054.37	64,297.98	63,770.15
GA	3,003,994.71	2,599,531.22	1,877,193.59	1,625,654.26
IA	145,313.80	139,695.94	196,387.16	188,948.54
ID	5,133.06	5,035.56	6,841.24	6,711.29
IL	72,759.72	70,089.46	296,087.65	287,178.57
IN	290,016.91	267,949.62	557,095.10	515,341.22
KS	587,250.75	472,857.08	563,982.08	462,603.78
KY	15,303.79	14,369.63	19,731.83	18,725.65
LA	0.00	0.00	0.00	0.00
MA	1,507.44	1,498.01	3,067.30	3,048.70
MD	987,370.38	756,043.24	593,751.90	457,342.43
ME	180,649.15	139,923.70	120,790.75	94,691.15
MI	873,340.24	737,304.98	1,669,807.32	1,413,673.32
MN	1,130,676.95	1,006,555.01	1,531,025.27	1,383,096.65
MO	0.00	0.00	0.00	0.00
MS	0.00	0.00	0.00	0.00
MT	354,100.96	278,938.20	613,331.65	488,154.28
NC	1,311,899.77	1,263,151.39	795,151.12	766,122.34
ND	116,076.31	105,652.62	683,805.25	622,728.97
NE	125,550.33	116,413.59	146,585.82	135,962.79
NH	0.00	0.00	0.00	0.00
NJ	44,893.10	43,908.07	111,881.82	109,473.59
NM	269,914.51	242,979.04	103,097.41	92,770.94
NV	0.00	0.00	0.00	0.00
NY	0.00	0.00	0.00	0.00
OH	503,733.66	469,204.89	856,893.92	800,621.67
OK	69,630.58	38,809.67	37,935.93	21,374.67
OR	220,382.82	205,163.52	619,381.99	577,956.25
PA	405,805.79	375,045.39	257,265.52	237,985.12
RI	896.09	880.24	2,067.75	2,033.41
SC	909,564.99	722,230.73	950,124.03	757,538.48
SD	280,468.83	250,374.61	534,982.32	483,169.41
TN	0.00	0.00	0.00	0.00
TX	73,925.96	46,312.89	53,758.76	33,715.75
UT	19,523.77	17,700.13	11,366.95	10,284.31
VA	87,676.83	64,205.79	61,057.59	44,771.25
VT	32,492.78	28,860.87	8,425.52	7,485.39
WA	258,201.76	252,399.10	591,869.72	578,671.04
WI	660,384.79	589,893.12	381,481.08	341,815.60
WV	272,753.29	219,250.34	120,709.36	97,234.34
WY	6,450.18	5,995.18	3,706.17	3,444.73
U.S	17,145,997.90	14,303,179.48	15,988,383.03	13,919,365.61

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Authors' contributions
TK, LEF and RKP together conceived of the project. TK conducted the analyses. TK, LEF and RKP interpreted the results and contributed to writing and approved the final manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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The authors declare that they have no competing interests.

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