The US Agriculture Greenhouse Emissions and Environmental Performance

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Introduction

Over the last decades it has been documented that agriculture is one of the most important contributors to greenhouse gas emissions. In fact, agriculture emits methane (CH_4) and nitrous oxide (N_2O). The potency of these greenhouse gases is measured by their Global Warming Potential (GWP) - a standardized measure of impact that compares the total warming effect of gas over a given time of period to the warming effect of carbon dioxide (CO_2). Methane's GWP is 21, meaning that one ton of CH_4 warms as much as 21 tons of CO_2. On the other hand, nitrous oxide has a GWP evaluated at 310 and a life time estimated at 115 years, making it more potent than both CH_4 and CO_2 in its ability to affect climate change (IPPC, 2007). Results from a recent study indicate that nitrous oxide is currently the leading ozone-depleting substance being emitted (A. R. Ravishankara, et al.2009).

Methane emission results from the natural digestive process of animals and manure management at livestock operations whereas nitrous oxide results from soil management and fertilizer use on croplands. It has been documented that 7,516 million metric tons per year of CO_2 equivalents (CO_2e), or 18 percent of annual worldwide GHG emissions, are attributable to livestock (FAO 2006). A more recent analysis advanced that livestock and their byproducts actually account for at least 32,564 million tons of CO2e per year, or 51 percent of annual worldwide GHG emissions (Robert Goodland and Jeff Anhang 2009). The projected expansion of livestock and crop production consecutive to population growth is, *ceteris paribus*, deemed to exacerbate air and water pollution, deforestation, land degradation, reduction of biodiversity. Livestock has been the major driver of deforestation as well as one of the leading drivers of land degradation, water and air pollution, climate change and overfishing, sedimentation of coastal area and facilitation of invasions by alien species (FAO, 2006).

In the United States, the agricultural sector emitted about 6 percent of total U.S. greenhouse gas emissions in 2009(EPA 2010). Methane emissions from livestock represent 34 percent of total CH_4 emissions from anthropogenic activities. Agricultural soil management activities such as fertilizer application and other cropping practices have been reported to be the largest source of N_2O emissions, accounting for 68 percent (EPA, 2010). Hence, agriculture has emerged as one the top two or three most significant contributors to the most serious environmental problems to deserve an attention in research and policymaking. On greenhouse gas emissions and climate change, the US agriculture sector is prompted to more regulation and legislations: Clean Air Act, Global Warming Reduction Act of 2006, Safe Climate Act of 2006, Climate Stewardship and Innovation Act of 2005, Regional Greenhouse Gas Initiative… The turning point of this legislation and regulation is the regulation of GHG emissions from stationary sources by the EPA under Clean Air Act. In virtue of this regulation, stationary sources (agriculture included) emitting more than 25, 000 metric tons of GHG per year will be required to obtain permits as of July 2011[1].

However, it is worth pointing out that the environmental impact of the agricultural sector is not only negative. As matter of facts, agriculture provides tremendous environmental services, such as biodiversity, flood and drought control, and sink for greenhouse gases. Given, both its impact on the environment and its economic importance, agriculture is a target for environmental policies.

Hence, environmental performance has gained a great interest in research and policymaking since the emerging concept of sustainable development with its corollaries environmental regulations.

To capture the environmental performance of the agricultural sector, number of tools has been developed parametric and non parametric. Data Envelopment Analysis (DEA), - non parametric-

[1] The reporting deadline for greenhouse gas emissions has been extended to 2012.

has emerged as one the most convenient approaches to assess environmental performance of decision making units (DMUs) producing jointly desirable outputs and non marketable undesirable outputs deprived of a price. In fact, the lack of price of undesirable outputs justified their ignorance in productivity accounting. But, most studies showed that not considering such by products underestimate performance of DMUs. Accounting for air pollution in measures of states manufacturing productivity growth, Färe, R., Grosskopf, S., and Pasurka,C. (2001) concluded that the productivity growth is higher when the undesirable outputs are accounted for. Byung and Sickles, R. (2004) found a little change in productivity growth analysis of the role of environmental factors in growth accounting of the OECD and Asian countries when the undesirable (carbon dioxide) output is considered. Hailu and Veeman (2000) analyzed the economic performance of the Canadian pulp and paper industry and concluded that the environmentally sensitive productivity growth estimates are higher than the conventional ones.

In the above studies the environmental DEA was conducted at the macro level and considered, the gross domestic production (GDP) as sole desirable output and carbon dioxide (CO2)nitrogen oxide (NO_X) and sulfur oxide (SO_X) emissions as undesirable outputs(Färe, R., Grosskpof, S., Hernandez-Sancho, F., 2004; Byung and Sickles, 2004). At the micro or sectorial level, most studies have been oriented to energy sector wherein the electricity generator facilities discharge sulphur dioxide, nitrogen oxide and carbon dioxide into the atmosphere. (Färe, R., Grosskopf, S., Tyteca, D., 1996; Tyteca 1997; Färe et al. 2004). Other sectors include the pulp and paper industry with biological oxygen demand and total suspended solids as major water pollutants (Hailu and Veeman 2000). In the manufacturing sector, undesirable outputs are mainly water and air pollutants (sulphur oxide (SOx), nitrogen oxide (NOx) and carbon monoxide (CO)).

On the other hand, most of studies on agricultural environmental performance have been focused on soil, water and biodiversity issues (Kellog et al. 2002; Ball et al. 2002; Chaston and Gollop 2002; OCDE 2008). Little interest has been directed to agriculture environmental performance with respect to greenhouse gas emissions.

The objective of this paper is to measure the US agriculture environmental performance with respect greenhouse gas emissions (methane and nitrous oxide, two gas endowed with very high global warming potential). To reach this objective, the paper opts for a non parametric approach and utilizes a graph measure of technical efficiency accounting for undesirable outputs proposed by Färe et al. (2008) and a Malmquist – Luenberger productivity index by Chung et al.(1997). The rest of the paper is organized as follow. The first section addresses the two approaches mentioned above. The second depicts the data set and discusses the results.

1. Environmental performance measurement approaches

To capture environmental performance, when a technology produces jointly desirable and undesirable outputs such as water and air pollutants, greenhouse gas and other environmentally bad outputs, multiple approaches can be used. But, the Data Envelopment Analysis approach has emerged as one of the most convenient because it does not neither require price information nor a specific functional form to describe the technology. For this specific case, the lack of undesirable output prices makes this approach very convenient. This paper uses a graph measure of technical efficiency and a Malmquist-Luenberger productivity index to account for undesirable outputs.

1.1 Graph Measure of Technical Efficiency accounting for undesirable outputs

This approach allows capturing technical efficiency under both strong and weak disposability of outputs. It also offers the benefit of assessing the effectiveness of regulation measures, in our case the US agricultural greenhouse emissions. Recall that starting from 2012 GHG emitters from stationary sources who do not currently have permits are required to obtain one under Title V of the Clean Air Act [2] for emission of CO2 in excess of 25, 000 metric tons of. This situation is assessed by positing the following two scenarios. The first one corresponds to the case where agricultural GHG emissions are not regulated, as is the case until the EPA requirements are imposed in July 2011 and imposes strong disposability in the technology set across all outputs. The second considers the same period but specifies a technology with weak disposability across outputs to simulate the regulatory effect.

Let define a production technology T transforming inputs $x \in R_{+}^{N}$ into desirable outputs $y \in R_{+}^{M}$ and undesirable outputs $b \in R_{+}^{J}$ such that $T = \{(x, y, b)$: *x can produce* $(y,b)\}$. This technology accounting for the undesirable outputs satisfies the following axioms:

1. Null –Jointness : This axiom states that production of desirable output has undesirable output as byproduct—if there is no undesirable output produced, there can be no desirable output. Thus no production can occur on the y-axis of the output set except at y=0. This axiom models joint production of desirable and undesirable outputs. Formally this assumption can be depicted as follow: if $(x, y. b) \in T$ and $b = 0$ then $y = 0$.

[2] The Clean Air Act(1970) is the comprehensive federal law that regulates air emissions from stationary and mobile sources. Among other things, this law authorizes the EPA to establish National Ambient Air Quality Standards (NAAQS) to protect public health and public welfare and to regulate emissions of hazardous air pollutants. Title V is related to permit requirements.

2. *Weak disposability* : This (indirectly) models the possibility that bad outputs may not be freely disposable, perhaps due to regulation. More formally, bad output is weakly disposable with good output if $(y, b) \in P(x)$, $(\lambda y, \lambda b) \in P(x)$, $0 \leqq \lambda \leqq 1$.

Note, however, that if P(x) satisfies strong disposability of (y, b), it also satisfies weak disposability of (y, b), where strong disposability holds if for $(y, b) \in P(x)$, $(y, b) \leqq (y', b') \in P(x)$.

This technology can be modeled by either output sets P(x) or input sets L (u). P(x) denotes all feasible outputs and $y \in R_+^M$ and $b \in R_+^N$ vectors obtainable from inputs $x \in R_+^N$. The Graph of the technology depicts all feasible input-output vectors and can be formally derived from the output correspondences as $GR = \{(x, y, b) \in R_+^{M+J} : y, b \in P(x), x \in R_+^N\}$. Conversely the output correspondences can be derived from the graph as $P(x) = \{y, b) \in GR\}$. Outputs can be partioned in a matrix M = ***(M^y,M^b)*** and subsequently a graph reference set under constant return to scale can be defined as $(GR/CS) = \{(x, y, b), y \leqq zM^y, b \leqq zM^b, zN \leqq x, z \in R_+^J\}$. Hence, two different graph efficiency measures can be defined depending on the disposability assumption.

Case 1. Efficiency Measurement under strong disposability

The function $F_g(x^k, y^k, b^k \mid C, S) = \min\{\lambda: (\lambda x^k, \lambda^{-1} y^k, \lambda b^k) \in (GR) \mid C, S)\}, k = 1,2 \dots K$ is defined as graph measure of technical efficiency accounting for undesirable outputs. This measure contracts equiproportionately and simultaneously undesirable outputs b^k and inputs x^k and expands desirable outputs y^k to $(\lambda x^k, y^k/\lambda, \lambda b^k)$ as depicted in Figure 1. In fact, for a given observation *k*, this measure computes the ratio of the maximum equiproportionate of undesirable output and input contraction as well as desirable output expansion in (GR/C, S).

This measure can be computed by solving the following non linear program problem:

$$F_g \; x^k, y^k, b^k \,I\, C, S \quad = min\lambda \qquad st: \; {}_{k=1}^{K} z_k{}' y_m^k \geq \lambda^{-1} y_m, \; m = 1, \ldots, M.$$

$$(1) \qquad {}_{k=1}^{K} z_k{}' b_j^k \leq \lambda b_j \;, \; j = 1, \ldots$$

$${}_{k=1}^{K} z_k{}' x_n^k \leq \lambda x_n \;, \; n = 1, \ldots, N$$

$$z_k{}' \geq 0, k = 1, \ldots K$$

This NLP can be converted in the linear programming problem below to simplify the computation.

$$(F_g \; x^k, y^k, b^k \,I\, C, S \;)^2 \quad = min\Gamma \qquad st: \; {}_{k=1}^{K} z_k{}' y_m^k \geq y_m, \; m = 1, \ldots, M.$$

$$(2) \qquad {}_{k=1}^{K} z_k{}' b_j^k \leq \Gamma b_j \;, \; j = 1, \ldots$$

$${}_{k=1}^{K} z_k{}' x_n^k \leq \Gamma x_n \;, \; n = 1, \ldots, N$$

$$z_k{}' \geq 0, k = 1, \ldots K$$

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

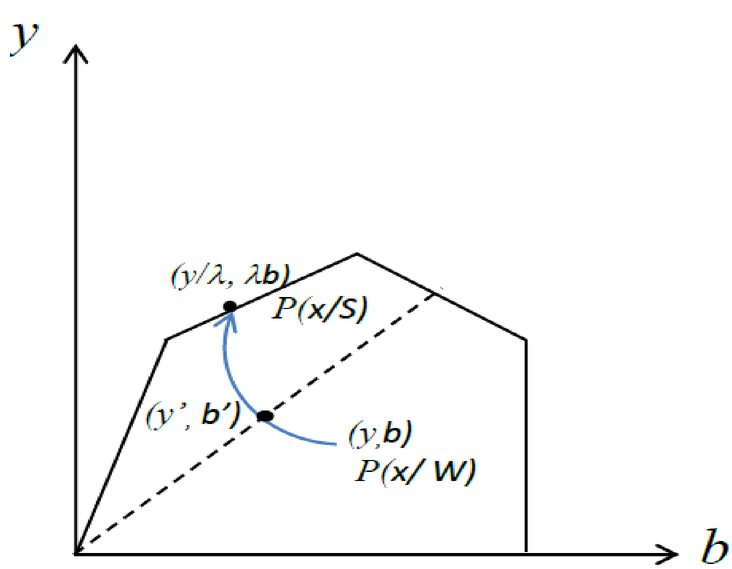


Figure 1: Strong and weak disposability

Case 2. Efficiency Measurement under weak disposability

Following Färe, et al. (1994) agricultural GHG emissions can be modeled as deviation from strong disposability of the undesirable outputs. This specification implies the treatment of undesirable as jointly and weakly disposable with the goods and the desirable output as strongly disposable. Under this specification the desirable output y is expanded to *y'* and the undesirable output *b* is contracted to b' as depicted in figure 1. The corresponding graph reference set can defined as

$(GR/C,W\ ) = \{(x,y,b), y \leqq zM^{y}, b \leqq \mu z M^{b}, zN \leqq x, \mu \in [0,1], z \in R_{+}^{J}\}$. Then, a Graph measure of technical efficiency can be defined as the function

$F_g\ x^k, y^k, b^k\ I\ C, W\ = \min\{\lambda: (\lambda x^k, \lambda^{-1} y^k, \lambda x b^k) \in (GR) I\ \ C, W)\}, k = 1,2 \ldots K$ and computed by solving the non linear programming problem below.

$$F_g\ x^k, y^k, b^k\ I\ C, W\ = min\lambda \qquad st: \ \sum_{k=1}^{K} z_k{}'\, y_m^k \leqq \lambda^{-1} y_m,\ m = 1, \ldots, M.$$

$$(3)\ \mu \sum_{k=1}^{K} z_k{}'\, b_j^k = \lambda b_j\ ,\ j = 1, \ldots J$$

$$\sum_{k=1}^{K} z_k{}'\, x_n^k \leqq \lambda x_n\ ,\ n = 1, \ldots, N$$

$$z_k' \geq 0, k = 1, \ldots K$$

$$0 \leqq \mu \leqq 1$$

Its correspondent linear form below is convenient for computation

$$(F_g\ x^k, y^k, b^k\ I\ C, W\ )^2 \quad = min\Gamma \qquad st: \sum_{k=1}^{K} z_k{}' y_m^k \geq y_m, \qquad m = 1, \ldots, M,$$

$$(4) \qquad \sum_{k=1}^{K} z_k{}' b_j^k = \Gamma b_j^{k\prime},\ j = 1, \ldots J$$

$$\sum_{k=1}^{K} z_k{}' x_n^k \leq \Gamma x_n^{k\prime},\ n = 1, \ldots, N$$

$$z_k{}' \geq 0, k = 1, \ldots K$$

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

The impact of the regulation can be determined in terms of potential desirable output lost or in terms of additional input required to offset the reduced disposability of the undesirable output from effective regulations. Given that the $F_g\ x^k, y^k, b^k\ I\ C, S \quad \leq F_g\ x^k, y^k, b^k\ I\ C, W$ the ratio of these two graph measures can be used to assess the effectiveness of the regulation. A ratio equivalent to one asserts the free disposability of the undesirable outputs and implies ineffectiveness of the regulation. On the other hand, if this ratio is less than one, the undesirable outputs are not freely disposable and the regulations in place are effective. More specifically this ratio is defined a the graph measure of output loss due to the lack of disposability of undesirable outputs Färe, et al.(2004).

$$C_g\ x^k, y^k, b^k \quad = F_g\ x^k, y^k, b^k\ I\ C, S \quad / F_g\ x^k, y^k, b^k\ I\ C, W$$

The percentage by which the desirable output could have been increased (given that $C_g\ x^k, y^k, b^k \quad < 1$) can be calculated by $1 - C_g\ x^k, y^k, b^k$ and represents a measure of the opportunity cost of binding regulation to the states.

1.2 The Malmquist-Luenberger Productivity Index

To grasp the ML productivity index, it is convenient to define a directional distance function. In the context of a joint production process of undesirable and desirable outputs, a directional distance function can be defined as follow:

$\boldsymbol{D_o^t}\ x^t, y^t, b^t; g_y, -g_b\ = Sup[\beta: (y + \beta g_y, b - \beta g_b) \in P^t(x^t)]$ where the $\boldsymbol{g} =\ g_y, -g_b$ is a vector determining the direction in which the desirable output is expanded and the undesirable output is contracted. β is the maximum feasible expansion of the desirable output and the contraction of the undesirable output when the expansion and the contraction are identical for a given level of inputs(FGP 2001). Visually, this direction distance function is depicted in Fig 2 where the point B is projected to C rather than to D in a case of a radial expansion.

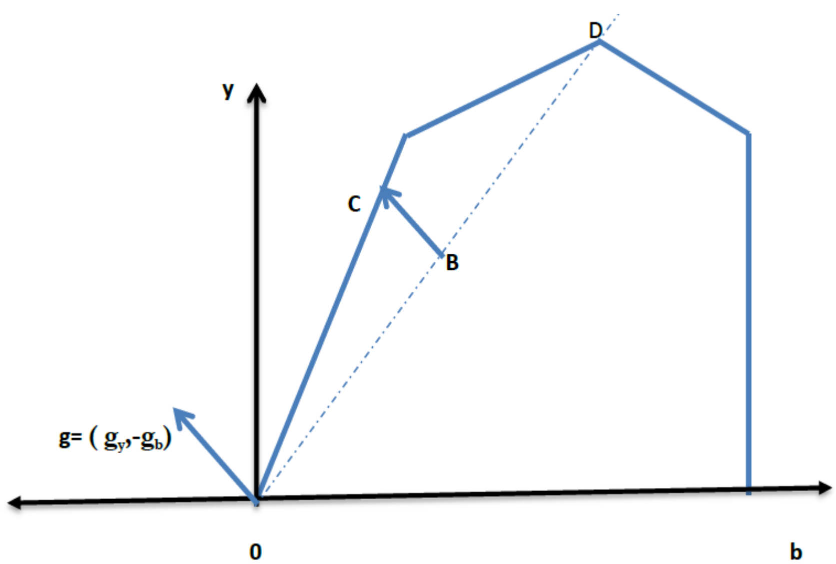


Fig. 2 Directional Distance Function

Having defined the directional distance function, the Malmquist-Luenbeger Productivity index with period t as technology reference is defined as follow:

$$5 \quad ML^t = [\frac{(1+D^t\ \ x^t, y^t, b^t; y^t, -b^t\ )}{(1+D^t\ \ x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\ )}]$$

Similarly, the Malmquist-Luenbeger Productivity index with period t +1 a technology reference is defined as follow:

$$6 \quad ML^{t+1} = [\frac{(1+D^{t+1}\ \ x^t, y^t, b^t; y^t, -b^t\ )}{(1+D^{t+1}\ \ x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\ )}]$$

Following Chung, et al.(1997) the Malmquist-Luenbeger Productivity index of interest is found by computing the geometric mean of the two aforementioned index as follow

$$7 \quad ML^{t,t+1}=[ML^{t} * ML^{t+1}]^{1/2} \ .$$

A $ML^{t,t+1}$. greater than one means that an improvement in productivity index from period t to period t +1. On the other hand, a $ML^{t,t+1}$. less than one means a decrease in productivity index. No change in productivity index is depicted by a $ML^{t,t+1}$ equal to one, where$x^{t} = x^{t+1}, y^{t} = y^{t+1}$ and $b^{t} = b^{t+1}$. This $ML^{t,t+1}$ can be decomposed in technical efficient change ($MLTE^{t,t+1}$) and technical change ($MLTC^{t,t+1}$) as follow:

$$8 \quad ML^{t,t+1}=MLTE^{t,t+1} * MLTC^{t,t+1}.$$

A $MLTC^{t,t+1}$. greater than one is interpreted as a shift of the production possibility frontier PPF in the direction of more desirable outputs and fewer undesirable outputs. On the other hand, a$MLTECH^{t,t+1}$. less than one depicts a shift of the PPF in the direction of more undesirable outputs and fewer desirable outputs. No shift in the PPF is represented by a $MLTC^{t,t+1}$. equivalent to one.

A $MLTE^{t,t+1}$ greater than one means that the production unit is closer to the frontier in period t+1 than it was in period t. Conversely, a $MLTEF^{t,t+1}$ less than one means that the production unit is further away from the to the frontier in period t+1 than it was in period t. A $MLTE^{t,t+1}$ equivalent to one indicated that production unit is positioned at the same distance on the frontier in both periods t and t+1.

Computing the ML productivity index requires 4 different distance functions. The following LP problem maximizes the value of the distance function of an observation k and the technology from the same period t.

$\boldsymbol{D_o^t}\ x^{k\prime t}, y^{k\prime t}, b^{k\prime t};\ g_y^{k\prime t},\quad g_b^{k\prime t}\quad = max\ \beta$

St $\quad {}_{k=1}^{K} z_k^t\, y_{km}^t \geq\ 1+\beta\ y_{k'm}^t,\quad m = 1, \dots, M$

9 $\quad {}_{k=1}^{K} z_k^t\, b_{kj}^t =\ 1-\beta\ b_{k'j}^t,\quad j = 1, \dots, J$

$\quad {}_{k=1}^{K} z_k^t\, x_{kn}^t \leq x_{k'n}^t,\quad n = 1, \dots, N$

$z_k^t \geq 0,\ k = 1, \dots K$

A maximal value of the distance function for an observation k from period t+1 using the technology from period t, is found by solving the following mixed period LP. The other distance functions can be computed similarly.

$\boldsymbol{D_o^t}\ x^{k't+1}, y^{k't+1}, b^{k't+1};\ g_y^{k't+1},\quad g_b^{k't+1}\quad = max\ \beta$

9 St $\quad {}_{k=1}^{K} z_k^t\, y_{km}^t \geq\ 1+\beta\ y_{k'm}^{t+1},\quad m = 1, \dots, M$

$\quad {}_{k=1}^{K} z_k^t\, b_{kj}^t =\ 1-\beta\ b_{k'j}^{t+1},\quad j = 1, \dots, J$

$\quad {}_{k=1}^{K} z_k^t\, x_{kn}^t \leq x_{k'n}^{t+1},\quad n = 1, \dots, N$

$z_k^t \geq 0,\ k = 1, \dots K$

To reduce the incidence of infeasible cases, this paper follows Färe, R., Grosskopf, S. and Pasurka, C. 2001 (2001) by using a multiple year windows of data as the technological reference. More specifically, the reference technology in period t is constructed with observations of time t-2, t-1 and t. Observations for period t-1, t and t+1 construct the reference technology in period t+1.

2. Data

The USDA's Economic Research Service (ERS) and the Environmental Protection Agency are sources of the data used in this paper for the period 1990-2004. The choice of this period is totally justified by the availability of data on both undesirable and desirable outputs. The desirable outputs and all inputs are indexes with Alabama =1 in 1996 as base. Crops and livestock are the two desirable outputs considered. Inputs consist of capital, land, labor, energy, chemical, pesticides and fertilizers. The undesirable outputs are methane(CH_4) and nitrous oxide (N_2O). Total N_2O is from managed systems of livestock by state in kg N_2O and from soil management in Gg CO_2 equivalent. Total methane is from rice cultivation and from livestock in Tg CO_2 Equivalents. All undesirable outputs were first converted into Tg CO_2 equivalents and then into a simple index of base 1996=1 for Alabama.

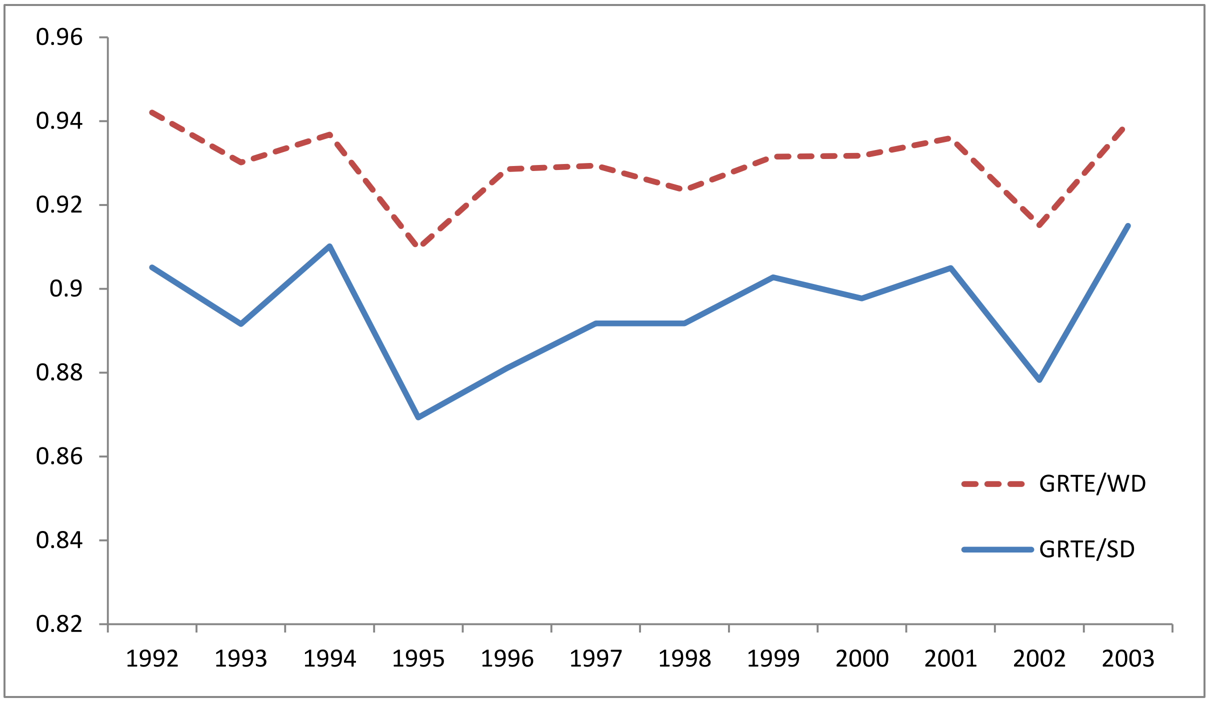
3. Results Discussion

3.1 Results from the Graph Measure of Technical Efficiency

The graph approach to measuring technical efficiency used in this paper provides three different measures: the graph measure of technical efficiency under strong disposability (GRTE/SD), the graph measure of technical efficiency under weak disposability (GRTE/WD) and the graph measure of output loss due to the lack of disposability of undesirable outputs (GROL).

On average both the GRTE/SD and GRTE/WD are less than one implying that the US agriculture is operating below the efficiency line regardless of the disposability of GHG assumptions. However, the efficiency under weak disposability – corresponding to a simulated regulated situation– is 0.03 higher than the one under strong disposability. In fact, deviating from strong to weak disposability results in efficiency improvement because technology to envelop data very closely so that observations are closer to the frontier. Under, strong disposability only one state is revealed efficient and 7 states under the weak disposability. This result is consistent with the one found by Chaston and Gallop (2002) in their study of the impact of water ground regulation on productivity growth. Since, regulation is modeled under weak disposability; one would expect the agriculture GHG regulations to improve environmental efficiency across states

Figure 3. US Average Graph Measure of Technical Efficiency under weak and Strong disposable 1992-2003



At the state level the GRTE/SD is ranged between 1 and .75. The best performance is attributed to Delaware and the worst to Texas. On the other hand, the GRTE/WD is ranged between 1 and .78 and the best performance is attributed to Delaware, Arizona, Florida, New-Hampshire, New-Jersey, New-Mexico, Rhode Island, Vermont and the worst to Texas.

The graph measure of output loss due to the lack of disposability of undesirable outputs (GROL) - the ratio of the GRTE/SD and GRTE/WD - is used here to simulate the impact of the regulation of the US agriculture GHG emissions. Result shows that on average, the GROL is less than one for all states but Delaware. This implies that if EPA has to regulate agricultural GHG emissions its regulations would be effective in the sense that it will induce a desirable output reduction in all states but Delaware. The percentage of desirable outputs to be forgone *ie* the opportunity cost of binding regulation to the DMUS, states in occurrence, is determined by deducting the GROL from one. This opportunity cost is zero for Delaware and ranged between 0.01 and 18% for the rest of states.

Table 2. Opportunity Cost (in % of desirable output) of Biding Agricultural GHG Emission Regulations

<1%	DE, CA, UT, VT, CT, NM, FL, CO, MA, NH, NC, IL, RI
1%-5%	ND, NV, AZ, VA, OK, MD, ID, NJ, KY, GA, KS, NE, AL, ME, PA, WA, TX, SD, IN, WV, OR, MN, NY, MS, SC
5%-10%	IA,TN, MI, MT,WI, OH, AR
>10%	WY, LA, MO

The highest loss cost could be endured by Wyoming, Louisiana and Missouri. Further results show that on average the GHG regulation could cost the US agriculture 3.7% reduction in desirable output. In other words, the US agricultural good output would have been increased by 3.7% if the states were not subject to agricultural GHG regulation.

Table 1. Average Graph Measure of TE under strong and weak disposability, Average Graph Measure of Output Loss and Opportunity Cost of binding regulation (1992-2003)

	GRTE/SD	GRTE/WD	GROL	Op. Cost
AL	0.875	0.900	0.972	0.028
AR	0.904	1.000	0.904	0.096
AZ	0.980	0.995	0.985	0.015
CA	0.998	0.999	0.999	0.001
CO	0.989	0.993	0.996	0.004
CT	0.999	0.999	0.999	0.001
DE	1.000	1.000	1.000	0.000
FL	0.998	1.000	0.998	0.002
GA	0.911	0.937	0.973	0.027
IA	0.945	0.998	0.947	0.053
ID	0.976	0.994	0.981	0.019
IL	0.985	0.993	0.992	0.008
IN	0.911	0.948	0.961	0.039
KS	0.873	0.899	0.972	0.028
KY	0.918	0.943	0.974	0.026
LA	0.758	0.904	0.838	0.162
MA	0.995	0.999	0.996	0.004
MD	0.900	0.916	0.982	0.018
ME	0.913	0.941	0.970	0.030
MI	0.838	0.900	0.931	0.069
MN	0.885	0.926	0.955	0.045
MO	0.802	0.981	0.818	0.182
MS	0.844	0.886	0.953	0.047
MT	0.759	0.828	0.918	0.082
NC	0.989	0.996	0.994	0.006
ND	0.914	0.926	0.988	0.012
NE	0.943	0.970	0.972	0.028
NH	0.995	1.000	0.995	0.005
NJ	0.978	1.000	0.978	0.022
NM	0.998	1.000	0.998	0.002
NV	0.987	0.999	0.987	0.013
NY	0.939	0.984	0.955	0.045
OH	0.862	0.950	0.909	0.091
OK	0.793	0.806	0.984	0.016
OR	0.941	0.981	0.959	0.041
PA	0.927	0.957	0.969	0.031

RI	0.991	1.000	0.991	0.009
SC	0.837	0.880	0.951	0.049
SD	0.880	0.915	0.961	0.039
TN	0.821	0.874	0.941	0.059
TX	0.751	0.781	0.961	0.039
UT	0.998	0.998	0.999	0.001
VA	0.855	0.869	0.984	0.016
VT	0.999	1.000	0.999	0.001
WA	0.965	0.998	0.967	0.033
WI	0.836	0.913	0.917	0.083
WV	0.923	0.962	0.960	0.040
WY	0.880	0.979	0.900	0.100
Average	**0.916**	**0.950**	**0.963**	**0.037**

3.2 The Malmquist-Luenberger Productivity Index Results

Although the use of the multiple windows of data to reduce the infeasibilities in the LP problem, 25 of the decisions-making units denote infeasible solutions. These DMUs are excluded from the reported results. The MLEC is less than one and suggests a loss in efficiency of 0.15 % in 2004 compared to 1990. In fact, producers moves further away from the contemporaneous benchmark technology in 2004 compared to 1990. The loss in efficiency over the considered period is 0.07% if the GHG emissions are ignored. The MLTC is greater than the unity and suggests a shift in a contemporaneous benchmark technology frontier in the direction of more desirable outputs and less undesirable outputs in 2004 compared to 1990. The shift is greater when the GHG emissions are accounted for. Production units for states like AZ, CA, CO, CT are positioned at the same distance on the frontier in both periods 1990 -2004 as shown by the unity value of the MLEC. Their improvement in productivity growth is mainly explained by the gain in technical change. The best performance on efficiency was recorded by WI with an efficiency gain of 0.8%, the worst by MT with an efficiency loss of 2.45%.

Table 3: US Agriculture Efficiency, Technical and Total Factor Productivity Change (1992-2003)

	MLTFPCH	MLEC	MLTC	TFPCH	EC	TC
	Accounting GHG Emissions			**Ignoring GHG Emissions**		
1992-93	1.0603	1.0308	1.0286	1.1051	1.0465	1.0560
1993-94	0.9356	0.9332	1.0025	0.9063	0.9080	0.9982
1994-95	1.0287	1.0121	1.0165	1.0237	0.9909	1.0331
1995-96	1.0009	1.0169	0.9843	0.9932	1.0415	0.9536
1996-97	1.0275	1.0123	1.0151	1.0133	1.0052	1.0080
1997-98	1.0189	1.0243	0.9947	1.0171	1.0506	0.9681
1998-99	1.0040	0.9784	1.0261	0.9972	0.9668	1.0314
1999-00	1.0043	0.9867	1.0178	1.0315	1.0150	1.0162
2000-01	0.9854	0.9731	1.0126	0.9579	0.9518	1.0065
2001-02	1.0719	1.0522	1.0187	1.1052	1.0861	1.0175
2002-03	1.0077	0.9689	1.0400	0.9937	0.9439	1.0528
Geometric Mean	**1.0125**	**0.9984**	**1.0141**	**1.0117**	**0.9992**	**1.0124**

21 out of 23 states recorded a shift of the contemporaneous benchmark technology frontier in the direction of more desirable outputs and fewer undesirable outputs as shown by the MLTC greater than one. CA hits the highest performance in technical progress with an improvement of 7.69 % followed by AZ 2.46 %, CT 3.49%, MN2.49 %, OR 2.32%, ME 1.20 % and TX 1.12 %. The worst performance is found in TN and KY with a regression in technical change of 0.19 and 0.18 % respectively.

The best performance in terms of TFP growth is recorded by CA with an increase of 7.69%, followed by MN 5.24%, CT 3.49%, and AZ 2.46% and OR 2.07%. This growth in productivity is mainly driven by technical change. MT, KS and KY showed a poor performance with a decline in productivity growth of 2.35%, 2.22% and 2.05% respectively.

A comparison of the MLTFP and the TFP ignoring GHG emissions reveals that the MLTFP, MLEC and the MLTC for the period 1990-2004 are higher than one ignoring the undesirable outputs on average (Table 3). However, across state comparison shows a pervasive result. In fact, 10 out of 23 states (GA, KS, KY, MT, ND, OK, SD, TX, and WI) have a lower productivity growth when the GHG emissions are accounted for. AL, SC, TN, TX and SD show a lower technical change when the undesirables are treated asymmetrically. This means the contraction of the GHG emissions for these states exceeds the expansion of the desirable outputs. The productivity growth of MI is invariant to an asymmetric treatment of the undesirable and the desirable outputs. But this invariance is only on the magnitude of the TFP growth but not in its components which reveals a gain in efficiency and a loss in technical change when a credit is given for reducing the GHG emissions. Hence, given that technical change is higher while ignoring the GHG emissions compared to the one accounting for them suggests that MI's expansion of desirable outputs exceeds the contraction of GHG emissions. This is the case for most states.

This improvement in productivity growth from the ML productivity index is consistent with the one in manufacturing sector in study conducted by Färe, R ,Grosskopf,S. and Pasurka, C. (2001). Other studies on agriculture found also higher environmental productivity growth (Ball, 2002). However, results from the ML productivity index come with a large number of infeasibilities which reduce the sample and narrow comparison across states.

Table 3: States Level Agriculture Efficiency, Technical and Total Factor Productivity Change (1992-2003)

States	MLTFPCH	MLEC	MLTC	TFPCH	EC	TC
	Accounting GHG Emissions			**Ignoring GHG Emissions**		
AL	1.0066	0.9989	1.0076	1.0010	0.9932	1.0078
AZ	1.0246	1.0000	1.0246	1.0000	1.0000	1.0000
CA	1.0769	1.0000	1.0769	1.0489	1.0000	1.0489
CO	1.0133	1.0000	1.0133	1.0091	1.0000	1.0091
CT	1.0349	1.0000	1.0349	1.0254	1.0006	1.0248
GA	1.0158	1.0030	1.0128	1.0273	1.0042	1.0230
KS	0.9778	0.9702	1.0078	1.0010	0.9800	1.0215
KY	0.9795	0.9814	0.9981	0.9828	0.9794	1.0035
MD	1.0170	1.0099	1.0070	1.0060	1.0178	0.9884
ME	1.0074	0.9955	1.0120	1.0058	0.9992	1.0067
MI	1.0075	1.0016	1.0059	1.0075	0.9962	1.0113
MN	1.0524	1.0268	1.0249	1.0647	1.0385	1.0252
MT	1.0178	0.9988	1.0190	1.0045	0.9952	1.0094
MT	0.9765	0.9753	1.0013	0.9875	0.9868	1.0007
ND	1.0105	0.9921	1.0185	1.0140	0.9868	1.0276
OK	1.0038	0.9995	1.0043	1.0088	0.9972	1.0116
OR	1.0207	0.9975	1.0232	1.0181	1.0060	1.0120
SC	1.0117	1.0045	1.0072	1.0069	0.9938	1.0131
SD	1.0115	1.0023	1.0093	1.0260	1.0035	1.0225
TN	1.0000	1.0018	0.9982	0.9929	0.9883	1.0045
TX	1.0037	0.9926	1.0112	1.0133	0.9963	1.0171
VA	1.0130	1.0061	1.0068	1.0076	1.0124	0.9953
WI	1.0117	1.0081	1.0036	1.0118	1.0091	1.0027
Geometric Mean	**1.0125**	**0.9984**	**1.0141**	**1.0117**	**0.9992**	**1.0124**

Concluding Remarks

This study aims at assessing the environmental performance the U.S. agriculture with respect to GHG emissions across states. To reach this objective, this paper utilizes alternative non-parametric approaches. The graph measure of technical efficiency accounting for undesirable outputs reveals that regulations of agriculture GHG emissions would be effective in all states but Delaware, as they would be binding and impose a 'cost' in terms of reduction of desirable output. Results show also that imposing weak disposability results in technical efficiency improvement of about 3.5%. States operating on the frontier shift from one to seven when the regulatory effect is simulated. But the opportunity cost of binding to this regulation could amount to 3.7% reduction of agricultural outputs under the same simulation. The Malmquist-Luenberger productivity index is higher than the one ignoring the undesirable outputs. But both are driven by technical change. To extend the comparison across states, further efforts are needed to reduce substantially the infeasibilities in the LP problem.

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