Water Pollution and Environmental Performance in US Agriculture

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Abstract

This paper appraises the environmental performance of US agriculture with respect to water pollution from pesticides through a parametric approach. The performance of the 48 continental States is evaluated through a translog stochastic and hyperbolic distance function allowing an environmentally adjusted productivity index and its components technical and efficiency change from 1960-1996. Water pollution is captured by four indicators of risk developed by Ball et al. (2004) : i) risk to human health from exposure to pesticide leaching; ii) risk to human health from exposure to pesticide runoff; iii) risk to aquatic life from exposure to pesticide leaching and iv) risk to aquatic life from exposure to pesticide runoff. The resulting environmentally adjusted productivity growth is slower than the conventional one but still driven by technical progress. Further finding reveals that innovation in the sector is biased toward crop and livestock rather than pollution mitigation. Results also show a potential for crops and livestock expansion and a contraction in water pollution and inputs.

1. Introduction

Agriculture has been a very successful sector of the U.S. economy in terms of productivity growth over the last six decades. From 1948 to 1994, productivity increased annually by 1.94 % reflected by a growth in output of 1.88 % and a decline in inputs of 0.06 % (Ahearn et al., 1998). But, this performance ignores byproducts and environmental impacts which include land degradation, climate change, and biodiversity loss and water pollution. In fact, agriculture emitted about 6.3% of total U.S. greenhouse gas emissions (EPA, 2012). Agricultural nonpoint source pollution is the leading source of water quality impacts on surveyed rivers and lakes, the second largest source of impairments to wetlands, and a major contributor to contamination of surveyed estuaries and ground water (FAO, 2006).

In US, the EPA (1990) national pesticide survey reveals that about 52.1% of the community water system wells contain nitrate, about 10.4% contain one or more pesticides, and about 7.1% contain both. On the other hand, 57% of rural domestic wells contain nitrate while 4.2% contain one or more pesticides, and about 3.2% contain both. More alarming, 0.8% of community water system wells and 0.6% of rural domestic wells contain one or more pesticides at levels above health-based limits. Further estimates show that approximately 1.2% and 2.4% respectively for community water system and rural domestic wells contain nitrate exceeding the health-based limits.

However, only very few studies have accounted for water contamination in the US agricultural productivity. Of the few studies, Ball *et al*. (2004) is most prominent but positing a strong assumption assimilating any deviation from the best frontier to inefficiency in a deterministic setting. Such approach also fails to provide statistical inference without a bootstrapping technique.

This study aims to assess the environmental performance of U.S. agriculture with respect to water pollution from pesticides following Ball et al. (2004) who used a non-parametric approach. Water pollution is captured by four indicators of risk developed by Ball et al. (2004) : i) risk to human health from exposure to pesticide leaching; ii) risk to human health from exposure to pesticide runoff; iii) risk to aquatic life from exposure to pesticide leaching and iv) risk to aquatic life from exposure to pesticide runoff. Results from this study reveal a drastic change in agricultural productivity growth when water contamination is accounted for. In fact, the conventional Malmquist productivity index (the one ignoring water contamination) reveals a 1.54% yearly growth whereas the environmentally sensitive hyperbolic average 0.98%. The ratio of the environmentally sensitive productivity index and the conventional one provides an environmental Malmquist productivity index that reveals a decline of growth to 0.56%. They also constructed two environmentally sensitive Fisher productivity indices -based on livestock and crops virtual prices- revealing growth rates of 1.25% and 1.43% per year over the period 1960-1996. Their Fischer environmental productivity growth rate is relatively higher than the environmentally sensitive Malmquist index growth rate but still smaller than the rate obtained with the conventional Malmquist index.

Table1. US States Agricultural Productivity Annual Growth Rates (1960-1996)

	Annual Growth Rates		
	CMPI*	**ESMPI****	**EPI*****
1960-1996	1.54%	0.98%	-0.56%
1960-1972	1.68%	-2.56%	-4.17%
1973-1983	0.12%	0.30%	0.18%
1984-1996	2.64%	4.96%	2.26%

Source Ball, et al. 2004

*Conventional Malmquist Productivity Index,
**Environmentally Sensitive Hyperbolic Malmquist Productivity Index
***Environmental Productivity Index= ESMPI/ CMPI

Ball et al.(2004) contrast the conventional Malmquist productivity index with three constructed environmental productivity indices accounting for water pollution from pesticide runoff into surface water and pesticide leaching into groundwater from 1960-1993. Results show an overestimation of productivity growth by the conventional Malmquist productivity index in the early years, and an underestimation in the later years. This bias is explained by failing to account for rapid increases in pesticide use and reductions in water contamination respectively in the earlier and later periods. Ball *et al.* (2001) also model the joint production of livestock and crop (desirable outputs) and water contamination (undesirable outputs) to calculate a Malmquist-Luenberger productivity index for US agriculture. Their results reveal a higher productivity growth when accounting for water contamination caused by the use of agricultural chemicals, especially in the later period of the study (1984-1993). Chaston and Gollop (2002) estimated a translog cost function to capture the impact of water regulation on US agricultural productivity. Results suggest that improvement in water quality subsequent to regulation substantially improved productivity.

2. Methodology

This study uses a parametric and stochastic hyperbolic distance function developed by Cuesta, Lovell and Zofio (2009) to account for water pollution in US agricultural productivity. This approach presents the advantage of treating desirable and undesirable outputs asymmetrically, conducting statistical inference without bootstrapping in contrast to non-parametric approaches, determining the desirable output elasticity with respect to the inputs, inputs substitutability or complementarity, and the degree of complementarity between desirable and undesirable outputs. Adding a time trend to the parametric setting serves as a proxy for technical progress.

The production technology can be defined as T transforming input vector $x_i = (x_{1i}, \dots x_{Ni}) \in R_+^N$ into output vectors $u_i = (u_{1i}, \dots u_{Pi}) \in R_+^P$ consisting of subvectors $y_i = (y_{1i}, \dots, y_{Mi}) \in R_+^M$ and $b_i = (b_{1i}, \dots, b_{Ji}) \in R_+^J$. y and b represent respectively desirable and undesirable outputs whereas the subscript $i = (1,2, \dots, S)$ refers to the decision making units, the 48 contiguous states in occurrence. From this definition, the technology T can be represented by a production possibility set as follows:

(1) $T = \{(x, y, b)\colon x \in R_+^N, (y, b) \in R_+^P, x \text{ can produce } (y, b)\}$

The technology can also be represented by an output distance function which represents the maximum feasible expansion of the desirable output vector required to reach the boundary of the technology T at a given level of inputs and undesirable outputs.

The output distance function $D_o\colon \Re_+^N \times \Re_+^M \times \Re_+^J \to \Re_+ U\{+\infty\}$ can be formally defined as:

$$(2) \quad D_O(x, y, b) = inf\left\{\phi > 0\colon \left(x, \frac{y}{\phi}, b\right) \in T\right\}$$

falling in the range of $0 \leq D_0(x, y, b) \leq 1$. To contract undesirable outputs while increasing desirable ones the technology can be represented by a hyperbolic distance function $D_H\colon \Re_+^N\ x\ \Re_+^M\ x\ \Re_+^J \to \Re_+ U\{+\infty\}$ formally defined as:

$$(3) \quad D_H(x, y, b) = inf\left\{\theta > 0\colon \left(x, \frac{y}{\theta}, \theta b\right) \in T\right\}$$

Here the hyperbolic distance function provides an environmental efficiency measure and represents the maximum expansion of the desirable output vector and equiproportionate contraction of the undesirable output vector that places a producer on the best practice frontier T. Its range is $0 \leq D_H(x, y, b) \leq 1$.

The enhanced hyperbolic distance function $D_E\colon \Re_+^N\ x\ \Re_+^M\ x\ \Re_+^J \to \Re_+ U\{+\infty\}$ is defined as

$$(4\,) \quad D_E(x, y, b) = inf\left\{\lambda > 0\colon \left(\lambda x, \frac{y}{\lambda}, b\lambda\right) \in T\right\}$$

with a range $0 \leq D_E(x, y, b) \leq 1$.

The enhanced hyperbolic distance function provides an environmental efficiency measure and represents the maximum expansion of the desirable output vector and equiproportionate contraction of the undesirable output and input vectors that places a producer on the best practice frontier T.

The $D_E(x, y, b, t\,)$ satisfies the following properties provided that the technology T satisfies the standard axioms as defined by Färe, Grosskopf and Lovell, (1985: 111) and Färe (1988:6-8)

1. Non decreasing in desirable outputs : $D_E(x, \lambda y, b, t) \leq D_E(x, y, b), \lambda \in [0,1]$

2. Non increasing in undesirable outputs :$D_E(x, y, \lambda b, t) \leq D_E(x, y, b), \lambda \geq 1$

3. Non increasing in inputs : $D_E(\lambda x, y, b, t) \leq D_E(x, y, b, t), \lambda \geq 1$

4. Almost homogeneity $D_E(\mu^{-1}x, \mu y, \mu^{-1}b, t)= \mu D_E(x, y, b, t)$, $\mu > 0$ The $D_E(x, y, b, t)$ is almost homogeneous of degree -1, 1, -1, 0 and 1respectively in undesirable outputs, desirable outputs, inputs, time trend and the distance function . This property implies that if the set of desirable outputs is increased by a given proportion while reducing the set of inputs and the undesirable outputs by the same proportion the function increases by that same proportion.

Following Cuesta and Zofio (2005) the almost homogeneity of $D_E(x, y, b, t)$ states that for a scalar $\mu > 0$ and any (x, y, b),

$$D_E\left(\frac{x}{\mu}, \mu y, \frac{b}{\mu}, t\right) = \inf\left\{\theta > 0 : \left(\frac{\theta x}{\mu}, \frac{\mu y}{\theta}, \frac{\theta b}{\mu}, t\right) \in T\right\}$$

$$= \inf\left\{\frac{\mu\theta}{\mu} > 0 : \left(\frac{\theta}{\mu}x, \frac{y}{\theta/\mu}, \frac{\theta}{\mu}\, b, t\right) \in T\right\}$$

$$= \mu\inf\left\{\frac{\theta}{\mu} > 0 : \left(\frac{\theta}{\mu}x, \frac{y}{\theta/\mu}, \frac{\theta}{\mu}\, b, t\right) \in T\right\}$$

$$= \mu D_E(x, y, b, t). \qquad (5)$$

A function $F(x, y, b, t)$ is almost homogenous of degree $k_1, k_2, k_3\, , k_4\; and\; k_5$ if

$$F(\mu^{k1}x, \mu^{k2}y, \mu^{k3}b, \mu^{k4}t,) = \mu^{k5}F(x, y, b, t), \forall\mu > 0. \qquad (6)\ldots$$

Assuming that $F(x, y, b, t)$ is continuously differentiable, to be almost homogeneous it must satisfy

$$k_1 \sum_{n=1}^{N} \frac{\partial F}{\partial x_n} x_n + k_2 \sum_{m=1}^{M} \frac{\partial F}{\partial y_m} y_m + k_3 \sum_{j=1}^{J} \frac{\partial F}{\partial b_j} b_j + k_4 \frac{\partial F}{\partial t} t = k_5 F. \qquad (7)$$

The output distance function $D_O(x, y, b, t\ )$ is almost homogeneous of degrees 0, 1, 0, 0 and 1. The hyperbolic distance function $D_H(x, y, b, t)$ is almost homogeneous of degrees 0, 1, −1, 0, and 1, and the enhanced the hyperbolic distance function $D_E(x, y, b, t)$ is almost homogeneous of degrees −1, 1, −1, 0 and 1.

Specify F(x, y, b, t) as a translog function for a panel of $i = 1 \ldots S$ producers as follows:

$$\ldots lnF$$

$$= \alpha_0 + \sum_{n=1}^{N} \alpha_n lnx_{ni} + \frac{1}{2}\sum_{n=1}^{N}\sum_{l=1}^{N} \alpha_{nl} lnx_{ni} lnx_{li} + \sum_{m=1}^{M} \beta_m lny_{mi}$$

$$+ \frac{1}{2}\sum_{m=1}^{M}\sum_{p=1}^{M} \beta_{mp} lny_{mi}\, lny_{pi}$$

$$+ \sum_{j=1}^{J} \gamma_j lnb_{ji} + \frac{1}{2}\sum_{j=1}^{J}\sum_{q=1}^{J} \gamma_{jq} lnb_{ji}\, lnb_{qi} + \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} lnx_{ni} lny_{mi} + \sum_{n=1}^{N}\sum_{j=1}^{J} \xi_{nj} lnx_{ni} lnb_{ji}$$

$$+ \sum_{m=1}^{M}\sum_{j=1}^{J} \tau_{mj} lny_{mi} lnb_{ji} + \eta_1 t + \frac{1}{2}\eta_2 t^2 + \sum_{n=1}^{N} \zeta_n lnx_{ni} t + \sum_{m=1}^{M} \varphi_m lny_{mi} t + \sum_{j=1}^{J} \pi_j lnb_{ji} t \quad (8)$$

Partial derivatives of $F(x, y, b, t)$ as defined in (8) yields the following elasticities:

$$\frac{\partial lnF}{\partial lnx_n} = \alpha_n + \sum_{n=1}^{N} \alpha_{nl} lnx_{ni} + \sum_{m=1}^{M} \delta_{nm} lny_{mi} + \sum_{j=1}^{J} \xi_{nj} lnb_{ji} + \zeta_n t, (n = 1,2, \ldots N)$$

$$\frac{\partial lnF}{\partial lny_m} = \beta_m + \sum_{p=1}^{M} \beta_{mp} lny_{pi} + \sum_{n=1}^{N} \delta_{nm} lnx_{ni} + \sum_{j=1}^{J} \tau_{mj} lnb_{ji} + \varphi_m t, (m = 1,2, \ldots N)$$

$$\frac{\partial lnF}{\partial lnb_j} = \gamma_j + \sum_{q=1}^{J} \gamma_{mp} lnb_q + \sum_{n=1}^{N} \xi_{nj} lnx_n + \sum_{j=1}^{J} \tau_{mj} lny_m + \pi_j t\,, (j = 1,2..J)$$

$$\frac{\partial lnF}{\partial lnt} = \eta_1 + \eta_2 t + \sum_{n=1}^{N} \zeta_n lnx_{ni} + \sum_{m=1}^{M} \varphi_n lny_{mi} + \sum_{j=1}^{J} \pi_j lnb_{ji} \qquad (9)$$

Dividing both sides of the equation (9), by $F(x, y, b, t)$ and imposing almost homogeneity of degrees -1 in input x, -1 in undesirable output b, 1 in desirable outputs y and zero in the time trend t , the translog function $F(x, y, b, t)$ defined in (7) yields the following:

$$(10) \quad \sum_{m=1}^{M} \frac{\partial F(.)}{\partial y_m} \frac{y_m}{F(.)} - \sum_{n=1}^{N} \frac{\partial F(.)}{\partial x_n} \frac{x_n}{F(.)} - \sum_{j=1}^{J} \frac{\partial F}{\partial b_j} \frac{b_j}{F(.)} = 1$$

Applying the almost homogeneity of degree −1, 1, −1, 0 and 1 to expression (7) and rewriting (10) in logarithmic form yields the following:

$$(10') \quad \sum_{m=1}^{M} \frac{\partial lnF}{\partial lny_m} - \sum_{n=1}^{N} \frac{\partial lnF}{\partial lnx_n} - \sum_{j=1}^{J} \frac{\partial lnF}{\partial lnb_j} = 1$$

Plugging all the partial derivatives obtained in (9) in equation $(10')$yields the following:

$$\begin{aligned}
&(11)\\
&\sum_{m=1}^{M} \left(\beta_m + \sum_{p=1}^{M} \beta_{mp} lny_p + \sum_{n=1}^{N} \delta_{nm} lnx_{ni} + \sum_{j=1}^{J} \tau_{mj} lnb_{ji} + \varphi_m t \right) \\
&- \sum_{n=1}^{N} \left(\alpha_n + \sum_{n=1}^{N} \alpha_{nl} lnx_{nl} + \sum_{m=1}^{M} \delta_{nm} lny_{mi} + \sum_{j=1}^{J} \xi_{nj} lnb_{ji} + \zeta_n t \right) \\
&- \sum_{j=1}^{J} \left(\gamma_j + \sum_{q=1}^{J} \gamma_{mp} lnb_q + \sum_{n=1}^{N} \xi_{nj} lnx_{ni} + \sum_{m=1}^{M} \tau_{mj} lny_{mi} + \pi_j t \right) = 1
\end{aligned}$$

From the previous equation, 1+N+M+J restrictions emerge as sufficient and necessary to ensure almost homogeneity of degrees -1, 1, -1, 0 respectively in inputs, desirable outputs, undesirable outputs and time trend:

$$\sum_{m=1}^{M} \beta_m - \sum_{n=1}^{N} \alpha_n - \sum_{j=1}^{J} \gamma_j = 1$$

$$\sum_{p=1}^{M}\beta_{mp}-\sum_{m=1}^{M}\delta_{nm}-\sum_{m=1}^{M}\tau_{mj}=0, \qquad m=1,2,\dots M \tag{12}$$

$$\sum_{n=1}^{N}\delta_{nm}-\sum_{n=1}^{N}\xi\alpha_{nl}-\sum_{n=1}^{N}\xi_{nj}=0, \qquad n=1,2,\dots N$$

$$\sum_{j=1}^{J}\tau_{mj}-\sum_{j=1}^{J}\xi_{nj}-\sum_{q=1}^{J}\gamma_{mp}=0 \qquad j=1,2,\dots J$$

$$\sum_{m=1}^{M}\varphi_{m}-\sum_{n=1}^{N}\zeta_{n}-\sum_{j=1}^{J}\pi_{j}=0$$

Recalling that $D_E\left(\frac{x}{\mu},\mu y,\frac{b}{\mu},t\right)=\mu D_E(x,y,b,t)$ by virtue of almost homogeneity and setting $\mu=\frac{1}{y_m}$ with y_m being an arbitrary chosen desirable output a translog enhanced hyperbolic function takes the following form:

$$\dots ln(D_E(x,y,b,t)/y_m)=$$

$$\alpha_0+\textstyle\sum_{n=1}^{N}\alpha_n\, lnx_{ni}^{*}+\sum_{m=1}^{M-1}\beta_m lny^{*}{}_{mi}+\sum_{j=1}^{J}\gamma_j lnb^{*}{}_{ji}$$

$$+\frac{1}{2}\sum_{n=1}^{N}\sum_{l=1}^{N}\alpha_{nl}lnx_{ni}^{*}\,lnx_{li}^{*}+\frac{1}{2}\sum_{m=1}^{M-1}\sum_{p=1}^{M-1}\beta_{nl}ny_{mi}^{*}lny_{pi}^{*}+\frac{1}{2}\sum_{j=1}^{J}\sum_{q=1}^{J}\gamma_{jq}lnb_{ji}^{*}lnb_{qi}^{*}$$

$$+\sum_{n=1}^{N}\sum_{m=1}^{M-1}\alpha_{nl}lnx_{ni}^{*}\,lny_{mi}^{*}+\sum_{n=1}^{N}\sum_{j=1}^{J}\alpha_{nj}lnx_{ni}^{*}\,lnb_{ji}^{*}+\sum_{m=1}^{M}\sum_{j=1}^{J}\tau_{mj}lny_{mi}^{*}\,lnb_{ji}^{*}$$

$$+\eta_1 t+\tfrac{1}{2}\eta_2 t^2+\textstyle\sum_{n=1}^{N}\zeta_n lnx^{*}{}_{ni}t+\sum_{m=1}^{M-1}\varphi_m lny^{*}{}_{mi}t+\sum_{j=1}^{J}\pi_j lnb^{*}{}_{ji}t \tag{13}$$

where ${y^*}_{mi} = y_{mi}/y_M$; ${b^*}_{ji} = b_{ji}y_M$ and ${x^*}_{ni} = x_{ni}y_M$. For all $y_m = Y_M$ the ratio ${y^*}_m$ is equal to one and vanishes since log of one is zero. Subsequently, all summation involving ${y^*}_m$ are over M-1.

In addition to almost homogeneity equation (13) satisfies the symmetry condition such that $\alpha_{nl} = \alpha_{ln}$, $\alpha_{nj} = \alpha_{jn}$, $\tau_{mj} = \tau_{jm}$ and $\gamma_{jq} = \gamma_{qj}$.

Opting for a stochastic frontier approach, any deviations from the frontier stem from two types of disturbances. Random disturbances such as factors beyond producers' control and error measurements are termed v_i hereafter. On the other hand, disturbances resulting from factors under producers' control such as technical and economic inefficiency are termed u_i hereafter, Aigner, Lovell and Schmidt (1977). In our specification, the inefficiency u_{it} corresponds to $ln(D_{Ei}(x,y,b,t))$ which ranges $-\infty < ln(D_{Ei}(x,y,b,t)) < 0$ for an interior solution. Producers operating along the frontier exhibit a $ln(D_{Ei}(x,y,b,t))$ equivalent to zero and are considered efficient. To account for errors in observations and measurement v_{it} is appended to equation (13) which turns into the following form:

$$-lny_{mi} = \alpha_0 + \textstyle\sum_{n=1}^{N}\alpha_n\, lnx^*_{ni} + \sum_{m=1}^{M-1}\beta_m ln{y^*}_{mi} + \sum_{j=1}^{J}\gamma_j ln{b^*}_{ji}$$

$$+\frac{1}{2}\sum_{n=1}^{N}\sum_{l=1}^{N} lnx^*_{ni}\, lnx^*_{li} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{p=1}^{M-1}\beta_{nl} ny^*_{mi} lny^*_{pi} + \frac{1}{2}\sum_{j=1}^{J}\sum_{q=1}^{J}\alpha_{jq} lnb^*_{ji} lnb^*_{qi}$$

$$+\sum_{n=1}^{N}\sum_{m=1}^{M-1}\alpha_{nl} lnx^*_{ni}\, lny^*_{mi} + \sum_{n=1}^{N}\sum_{j=1}^{J}\alpha_{nj} lnx^*_{ni}\, lnb^*_{ji} + \sum_{m=1}^{M-1}\sum_{j=1}^{J}\tau_{mj} lny^*_{mi}\, lnb^*_{ji}$$

$$+\eta_1 t + \frac{1}{2}\eta_2 t^2 + \sum_{n=1}^{N}\zeta_n ln{x^*}_{ni} t + \sum_{m=1}^{M-1}\varphi_m ln{y^*}_{mi} t + \sum_{j=1}^{J}\pi_j ln{b^*}_{ji} t$$

$$+v_{it} - u_{it} \quad (14)$$

This translog stochastic frontier can then be formulated in a more compact form as follows:

$$-lny_M = TL(x^*{}_{it}, y^*{}_{it}, b^*{}_{it};\ \alpha, \beta, \gamma, \delta, \xi, \tau, \pi) + \varepsilon_{it} \quad (14')$$

where $ln\left(D_{E_i}(x, y, b, t)\right) = -u_{it}$ and $\varepsilon_{it} = v_{it} - u_{it}$ with $v_{it} \sim N(0, \sigma_v{}^2)$ and $u_{it} \sim N^+(0, \sigma_u{}^2)$. The error ε_{it} has two components: i) a symmetric error v_{it} accounting for the stochastic nature of the production process and possible measurement errors of the inputs and outputs also assumed normally and identically distributed as $v_{it} \sim N(0, \sigma_v{}^2)$; ii) an asymmetric error u_{it} accounting for inefficiency and assumed to have a half normal distribution $u_{it} \sim N^+(\delta z_{it}, \sigma_u{}^2)$. z_{it} is a vector of explanatory variables associated with the technical inefficiency u_{it} . Both u_{it} and v_{it}terms are assumed to be independently distributed such that $\sigma_{vu} = 0$. δ is a vector of unknown coefficients.

Parameters of interest in the stochastic frontier model (14′) $B = (\alpha, \beta, \gamma, \delta, \xi, \tau, \pi)$ will be estimated by maximum likelihood principle. Since u_{it} cannot be directly estimated, the distribution function or the density function of ε_{it} is to be determined first. Thus, a conditional distribution of u_{it} given ε_{it} can be estimated as the conditional expectation of u_{it} given ε_{it}. Finally, the estimated technical efficiency for a decision making unit at time t can be formulated as

$$(15) \quad \widehat{TE}_{it}(x_{it}, y_{it}, b_{it}) = e^{-E(u_{it}|\hat{\varepsilon}_{it})} = e^{-\hat{u}_{it}}.$$

On the other hand, ε_{it} can be estimated as:

$\widehat{\varepsilon_{it}} = lny_{it} - lnf(x_{it}; \hat{\beta})$. of u_{it}.

The percentage of total error variance due to inefficiency can be determined as follows:

$$\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2} = \frac{\sigma_u^2/\sigma_v^2}{\sigma_u^2/\sigma_v^2+\sigma_v^2/\sigma_v^2} = \frac{\lambda^2}{\lambda^2+1} \qquad (16)$$

It can be shown that a lambda greater than 1 suggests than the variance for efficiency is dominated by the variance of the random errors.

Having determined the technical efficiency $\widehat{TE_{it}}(x_{it}, y_{it}, b_{it})$ as in (15), the efficiency change (EC) index between two adjacent periods $t-1$ and t can be computed as follows:

$$\widehat{EC} = \frac{\widehat{TE_{it}}(x_{it}, y_{it}, b_{it})}{\widehat{TE_{it-1}}(x_{it-1}, y_{it-1}, b_{it-1})} \qquad (17)$$

An $\widehat{EC}$ equivalent to one expresses no change in efficiency. On the other hand, $\widehat{EC}$ greater than one suggests an improvement in efficiency whereas a value of $\widehat{EC}$ less than one conveys a regress.

On the other hand, the technical progress is computed by partial derivative of equation (14) with respect to time as follows:

$$\widehat{TP_{it}} = -\frac{\partial lny_m}{\partial t} = \eta_1 + \eta_2 t + \sum_{n=1}^{N} \zeta_n lnx^*{}_{ni} + \sum_{m=1}^{M-1} \varphi_m lny^*{}_{mi} + \sum_{j=1}^{J} \pi_j lnb^*{}_{ji} \quad (18)$$

The technical change for the adjacent periods ($t-1$ and t) is computed as geometric mean of the two partial derivatives which corresponds to the exponential of their arithmetic mean in the case of a translog function. Coelli et al. (2005).

$$\widehat{TC}_{it} = exp\left\{\frac{1}{2}\left[\frac{\partial lny_{mit-1}}{\partial t-1} + \frac{\partial lny_{mit}}{\partial t}\right]\right\} \qquad (19)$$

A technical change $\widehat{TC}_{it}$equivalent to one shows stagnation or no progress. Technical progress is expressed by $\widehat{TC}_{it}$ greater than one whereas a regress is shown by a value less than one.

The Malmquist total factor productivity change can be calculated as a product of the two previous measures if the technology exhibits constant return to scale or as follows:

$$\widehat{TFP}change = \widehat{TC} * \widehat{TEC} * \widehat{SC} \qquad (20)$$

To account for scale economies the inclusion of a scale change as a third component of the TFP index is suggested by Denny, Fuss and Waverman (1981) cited by Coelli et al. (2005), Balk (2001) and Orea (2002) extend it to a parametric distance function.

$$\widehat{SC} = \exp\left\{\frac{1}{2}\sum_{n=1}^{N}[\epsilon_{nit-1}SF_{it-1} + \varepsilon_{nit}SF_{it}]\ln(x_{nit}/x_{nit-1})\right\} \qquad (21)$$

where $SF_{it-1} = (\epsilon_{nit-1} - 1)/\epsilon_{nit-1}$, $\epsilon_{nit-1} = \sum_{n=1}^{N}\epsilon_{nit-1}$ and $\epsilon_{nit-1} = -\frac{\partial lny_{it-1}}{\partial lnx_{nit-1}}$

$SC = 1, SC > 1$ and $SC < 1$ characterize constant, increasing and decreasing return to scale respectively.

Prior to the interpretation and discussion of the results from the translog distance function defined in (14), we will first check the regularity properties of monotonicity and curvature. Key derivatives to gauging monotonicity are elasticities of the output distance function. Following O'Donnell and Coelli (2005), the $D_E(x, y, b, t)$ monotonicity requires that:

1. the $D_E(x, y, b, t)$ be non-increasing inputs:

$$d_n = \frac{\partial D_E(x,y,b,t)}{\partial x_n} = \frac{\partial lnD_E(x,y,b,t)}{\partial lnx_n}\frac{D_E}{x_n} = \epsilon_x \frac{D_E}{x_n} \le 0 \iff \boldsymbol{\epsilon_x} \le 0 \qquad (22a)$$

2. the $D_E(x, y, b, t)$ is non-increasing undesirable outputs

$$d_j = \frac{\partial D_E(x,y,b,t)}{\partial b_j} = \frac{\partial lnD_E(x,y,b,t)}{\partial lnb_j}\frac{D_E}{b_j} = \epsilon_x \frac{D_E}{b_j} \le 0 \iff \epsilon_{\boldsymbol{b}} \le 0 \qquad (22b)$$

3. the $D_E(x, y, b, t)$ is non-decreasing in desirable outputs

$$d_m = \frac{\partial D_E(x,y,b,t)}{\partial y_m} = \frac{\partial lnD_E(x,y,b,t)}{\partial lny_m}\frac{D_E}{y_m} = \epsilon_y \frac{D_E}{y_m} \ge 0 \iff \epsilon_{\boldsymbol{y}} \ge 0 \qquad (22c)$$

therefore the $D_E(x, y, b, t)$ monotonicity property amounts to having $\boldsymbol{\epsilon_y} \ge 0$; $\boldsymbol{\epsilon_b} \le 0$ and $\boldsymbol{\epsilon_x} \le 0$.

For a twice differentiable $D_E(x, y, b, t)$, quasi-convexity in $\boldsymbol{x}$ requires that all the principal minors of boarded Hessian Matrix HBD_x be non-positive ie $|HBD_{x1}| < 0$, $|HBD_{x2}| < 0, \dots$, $|HBD_{xN}| < 0$.

$$|HBD_{x1}| = \begin{vmatrix} 0 & d_1 \\ d_1 & d_{11} \end{vmatrix}, \ |HBD_{x2}| = \begin{vmatrix} 0 & d_1 & d_2 \\ d_1 & d_{11} & d_{12} \\ d_2 & d_{21} & d_{22} \end{vmatrix}, \dots, \ |HBD_{xN}|$$

$$HBD_x = \begin{bmatrix} 0 & d_1 & d_2 & & d_N \\ d_1 & d_{11} & d_{12} & \cdots & d_{1N} \\ d_2 & d_{21} & d_{22} & & d_{2N} \\ & \vdots & & \ddots & \vdots \\ d_N & d_{N1} & d_{N2} & \cdots & d_{NN} \end{bmatrix}$$

For a twice differentiable $D_E(x, y, b, t)$, convexity in $\boldsymbol{y}$ requires that all the principal minors of the Hessian Matrix HD_y be non-negative ie $|HBD_{y1}| \geq 0$,$|HBD_{y2}| \geq 0, \dots$, $|HBD_{yM}| \geq 0$ where

$$|HBD_{y1}| = \begin{vmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{vmatrix}, \ |HBD_{y2}| = \begin{vmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{vmatrix}, \dots, \ |HBD_{yM}|$$

$$HBD_y = \begin{bmatrix} d_{11} & d_{12} & d_{13} & & d_{1M} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2M} \\ d_{31} & d_{32} & d_{33} & & d_{3M} \\ & \vdots & & \ddots & \vdots \\ d_{M1} & d_{M12} & d_{M3} & \cdots & d_{MM} \end{bmatrix}$$

For a twice differentiable $D_E(x, y, b, t)$, quasi-convexity in $\boldsymbol{b}$ requires that all the principal minors of boarded Hessian Matrix HBD_x be non-positive ie $|HBD_{b1}| < 0$, $|HBD_{b2}| < 0, \dots$, $|HBD_{bN}| < 0$.

$$HBD_b = \begin{bmatrix} 0 & d_1 & d_2 & & d_J \\ d_1 & d_{11} & d_{12} & \cdots & d_{1J} \\ d_2 & d_{21} & d_{22} & & d_{2J} \\ & \vdots & & \ddots & \vdots \\ d_J & d_{J1} & d_{J2} & \cdots & d_{JJ} \end{bmatrix}$$

3. Data and Results Discussion

This study uses a panel data set from the 48 contiguous states over the period 1960 – 1997. Desirable output is an index of all outputs (crop, livestock and other farm-related outputs) whereas inputs are indices of capital, land, labor, and intermediate inputs. Methods and documentation of these indices can be explored in Ball, Wang and Nehring (2010). Water pollution is captured through four indicators of risk to human health and to aquatic life arising from exposure to pesticide runoff into surface water and pesticide leaching into groundwater developed by Kellog *et al*. (2002). These indices are: i*)* index of risk to human health from exposure to pesticide leaching; *ii)* index of risk to human health from exposure to pesticide runoff; *iii)* index of risk to aquatic life from exposure to pesticide leaching and *iv)* index of risk to aquatic life from exposure to pesticide runoff.

Table 2. Data* Descriptive Statistics: State-Level U.S. Agricultural Data, 1960-1997

Variables	**Mean**	**Std Dev**	**Min**	**Max**
y1 Output Production Index	1.0673	1.0648	0.0127	8.3548
b1 IR_HPL	0.5843	1.1331	0.0000	14.6001
b2 IR_HPR	7.3091	17.3647	0.0000	140.5140
b3 IR_APL	0.6480	1.5511	0.0000	17.9762
b4 IR_ APR	0.7599	1.2647	0.0000	16.4965
x1 Capital	1.9341	1.7269	0.0219	9.4096
x2 Land	2.1244	2.2344	0.0118	15.1196
x3 Labor	2.7514	2.3796	0.0285	12.5889
x4 Intermediate Inputs	0.8537	0.8003	0.0067	8.0000

Source: ERS 2010 and Ball et al. 2004.
**All data are indexed to Alabama 1996=1*
IR_HPL =Index of Risk to Human Health from exposure Pesticide Leaching
IR_HPR =Index of Risk to Human Health from exposure Pesticide Runoff
IR_APL =Index of Risk to Aquatic Life from exposure Pesticide Leaching
IR_APR = Index of Risk to Aquatic Life from exposure Pesticide Runoff

The authors assess the risk based on the extent to which the concentration of a specific pesticide exceeds a water quality threshold. To handle the translog estimation some zeros values in undesirable outputs were substituted by a value of 0.00001. The underlying argument for substitution is the jointness of water pollution and livestock and crops production. The zero pollution simply means there is very little pollution rather than inexistence. If the zeros occur by nonexistence, quadratic function comes as an alternative to the translog used in this study. Battese (2008) suggests another alternative but in the Cobb Douglas production setting. To account for pesticide regulation impacts on efficiency levels, we included three dummies; the first one considers the inception of the EPA as regulatory body, the second accounts for the 1972 EPA regulation regarding use of DDT and the third for the EPA's 1983 ban on toxaphene. To account for fixed effects, we use 9 dummies for the 10 US regions used by USDA (Northeastern plains, Appalachian plains, Lake States, Cornbelt plains, Delta States, Northern plains, Southern States, Mountain, and Pacific States

The parametric distance function is estimated with the package frontier within R software developed by Coelli and Henningsen (2012). We first check the key regularity conditions of monotonicity and curvature of the output distance function $D_E(x, y, b, t)$. The former stipulates that the $D_E(x, y, b, t)$ is non-decreasing in desirable outputs y and non-increasing in inputs x and undesirable outputs b. The latter requires that $D_E(x, y, b, t)$ be quasiconvex in x and b and convex in y. The overall monotonicity check reveals that the distance function is monotonically increasing in all arguments for 0.1%, with different levels of violations in inputs and outputs. Intermediate inputs exhibit the lowest violation rate of 0.1% followed by capital (6.9%). Labor and land are characterized by violation rate of 20.8% and 71.9% respectively. For undesirable outputs, the highest violation rate is found in the IR_APL (74.6%). The IR_HPL and the IR_HPR are characterized by a violation of 26.8% and 16.5% respectively. It follows that the elasticities of the $D_E(x, y, b, t)$ with respect to land (0.0163) and INDX-FL (0.0019) are not consistent with monotonicity condition as IR_HLP , IR_HRP, capital labor and intermediate input displayed in the unrestricted estimates of table 3. The curvatures check shows that $D_E(x, y, b, t)$ is quasi- convex in y only on 6.7% data points. Consistent with theoretical properties of the distance function we first impose monotonicity using a three step procedure proposed by Henningsen and Henning (2009).

Table 3 Output Distance Elasticities, U.S. agriculture, 1960-1997

(Equation 22)

	Violating Monotonicity	***Fulfilling Monotonicity***

Output_Index ($\epsilon_{\boldsymbol{y}}$)	1.0322	0.9773
IR_HLP ($\epsilon_{\boldsymbol{b1}}$)	-0.0084	-6.91E-16
IR_HRP ($\epsilon_{\boldsymbol{b2}}$)	-0.0306	-0.0227
IR_ALP($\epsilon_{\boldsymbol{b2}}$)	-0.0032	-1.60E-17
Capital ($\epsilon_{\boldsymbol{x1}}$)	-0.1078	-0.0988
Land ($\epsilon_{\boldsymbol{x2}}$)	0.0254	-0.0124
Labor ($\epsilon_{\boldsymbol{x3}}$)	-0.0199	-0.0295
InterInput ($\epsilon_{\boldsymbol{x4}}$)	-0.3820	-0.3614

Source: Author's calculation

On the first step, we estimate the translog stochastic frontier and check the monotonicity and curvature properties as pointed out earlier. Estimates for this initial step are reported in table 9(see appendix).

On the second step, we extract the estimated parameters $\widehat{\mathrm{B}}$ and their corresponding covariance matrix Σ_{B} to conduct a minimum distance estimation as follows:

(23) $\widehat{\mathrm{B}}^{o} = \arg\min\left(\widehat{\mathrm{B}}^{o} - \widehat{\mathrm{B}}\right)\hat{\Sigma}_{\mathrm{B}}^{-1}\left(\hat{B}^{o} - \hat{B}\right)$

subject to $f_i\left(x; \widehat{\mathrm{B}}^{o}\right) \geq 0 \; \forall i, x$

For our translog output distance function, this constraint turns into

$TL_i\left(X; \widehat{\mathrm{B}}^{o}\right) = \frac{TL\left(X, \widehat{\mathrm{B}}^{o}\right)}{\partial X_i} \leq 0$ where $X = (x, b)$

This can be converted into the following quadratic program problem

(24) $s^{*} = arg\min_{s} \boldsymbol{c}'\boldsymbol{s} + \frac{1}{2}\boldsymbol{s}'Q\boldsymbol{s}$ st $As \leq \boldsymbol{b}$

where $\boldsymbol{s} = (\widehat{\mathrm{B}}^{o} - \widehat{\mathrm{B}})$, $\boldsymbol{c} = (\boldsymbol{0}, \dots, \boldsymbol{0})$, $Q = \hat{\Sigma}_{\mathrm{B}}^{-1}$, $A \leq R$ and $\boldsymbol{b} = -\boldsymbol{R}\widehat{\mathrm{B}}$ from the quadratic programming the restricted parameters $\widehat{\mathrm{B}}^{o}$ can be determined as

$\widehat{\mathrm{B}}^{o} = s^{*} + \widehat{\mathrm{B}}$

$\boldsymbol{R}\mathbf{B} \leq \mathbf{0}$ where $\mathbf{R}$ represents a matrix of dimension $n * (1 + \frac{n(n+3)}{2})$ and n is the number of variables in the output distance function.

$$
\boldsymbol{R} = \begin{bmatrix} \mathbf{0} & \mathbf{1} & \mathbf{0} & \cdots & \mathbf{0} & \boldsymbol{lnX_1} & \boldsymbol{lnX_2} & \cdots & \boldsymbol{lnX_n} & \mathbf{0} & \cdots & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & \cdots & \mathbf{0} & \mathbf{0} & \boldsymbol{lnX_1} & \cdots & \mathbf{0} & \boldsymbol{lnX_2} & \cdots & \boldsymbol{lnX_n} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{1} & \mathbf{0} & \mathbf{0} & \cdots & \boldsymbol{lnX_1} & \mathbf{0} & \cdots & \mathbf{0} & \cdots & \boldsymbol{lnX_n} \end{bmatrix}
$$

$$
\mathbf{B} = (\beta_0, \beta_1, \beta_2, \ldots \beta_n, \beta_{11}, \beta_{12}, \ldots \beta_{1n}, \beta_{22}, \ldots, \beta_{2n}, \ldots, \beta_{nn})'
$$

Table 4 Monotonic Restricted Coefficient from the Minimum Distance Estimation

Variables	**Restricted Coefficients(Eq 23)**	**Difference (Restricted-Unrestricted)**	**Restricted_adjusted coefficient(eq 28)**
Intercept	-0.3772	-0.1763	0.3774
IR_HPL	0.0030	0.0696	-0.0030
IR_HPR	0.0186	-0.0827	-0.0186
IR_APL	0.0000	-0.0176	0.0000
Capital	0.2960	0.4717	-0.2962
Land	0.0194	-0.0300	-0.0194
Labor	0.0339	0.0473	-0.0339
InterInput	0.1760	0.6153	-0.1761
Time	0.0045	0.0061	-0.0045
*IR_HPL*IR_HPL*	0.0001	0.0023	-0.0001
*IR_HPL*IR_HPR*	-0.0001	-0.0025	0.0001
*IR_HPL*IR_APL*	0.0000	-0.0002	0.0000
*IR_HPL*Capital*	-0.0002	-0.0255	0.0002
*IR_HPL*Land*	-0.0002	-0.0012	0.0002
*IR_HPL*Labor*	-0.0005	-0.0079	0.0005
*IR_HPL*InterInput*	0.0010	0.0357	-0.0010
*IR_HPL*Time*	0.0000	-0.0002	0.0000
*IR_HPR*IR_HPR*	0.0025	0.0165	-0.0025
*IR_HPR*IR_APL*	0.0000	0.0003	0.0000
*IR_HPR*Capital*	-0.0098	-0.0021	0.0098
*IR_HPR*Land*	0.0005	0.0229	-0.0005
*IR_HPR*Labor*	0.0024	0.0108	-0.0024

Source: Author’s Calculations

Table 4(continued) Monotonic Restricted Coefficient from the Minimum Distance Estimation

Variables	Restricted Coefficients(Eq 23)	Difference (Restricted-Unrestricted)	Restricted_adjusted coefficient(eq 28)
*IR_HPR*InterInput*	0.0055	-0.0406	-0.0055
*IR_HPR*Time*	-0.0004	-0.0006	0.0004
*IR_APL*IR_APL*	0.0000	0.0000	0.0000
*IR_APL*Capital*	0.0000	0.0076	0.0000
*IR_APL*Land*	0.0000	0.0009	0.0000
*IR_APL*Labor*	0.0000	0.0028	0.0000
*IR_APL*InterInput*	0.0000	-0.0105	0.0000
*IR_APL*Time*	0.0000	0.0002	0.0000
*Capital*Capital*	-0.0644	-0.0788	0.0645
*Capital*Land*	-0.0123	-0.0871	0.0123
*Capital*Labor*	-0.0412	-0.0857	0.0413
*Capital*InterInput*	0.1055	0.2294	-0.1056
*Capital*Time*	-0.0018	-0.0040	0.0018
*Land*Land*	-0.0047	-0.0513	0.0047
*Land*Labor*	0.0045	0.0119	-0.0045
*Land*InterInput*	0.0122	0.1063	-0.0122
*Land*Time*	-0.0002	-0.0016	0.0002
*Labor*Labor*	0.0036	-0.0163	-0.0036
*Labor*InterInput*	0.0305	0.0784	-0.0305
*InterInput*Time*	0.0001	-0.0001	-0.0001
*InterInput*InterInput*	-0.1265	-0.3503	0.1266
*InterInput*Time*	0.0020	0.0057	-0.0020
*Time*Time*	0.0002	0.0005	-0.0002

Source : Author's Calculation

On the third step a stochastic frontier is estimated where the initial dependent variable$-lny$ is regressed on the predicted $ln\tilde{y}$ based on the restricted estimates.

$$(26) \quad -lny = \alpha_0 + \alpha_1 ln\tilde{y} - u^o + v^0$$

where $-ln\tilde{y} = TL(x, y, b; \widehat{\mathrm{B}}^o)$, $u^o = \delta z$. (26) amounts to allowing an adjustment of the restricted frontier $\frac{1}{y} = e^{\alpha_0} f\left(x, b, y; \widehat{\mathrm{B}}^o\right)^{\alpha_1}$. The restricted and adjusted elasticities show that the $D_E(x, y, b, t)$ is non-increasing in both inputs and undesirable outputs as required by monotonicity property (see table 4).

Table 5. Stochastic frontier estimates (eq.26) based on monotonic restricted estimates

	Estimates	**Std- error**	
Intercept	-0.0508	(0.0054)	***
$ln\tilde{y}$	-1.0007	(0.0019)	***
EPA_Inception	-0.1103	(0.0499)	*
1972_Pesticide Regulation	-0.302	(0.0542)	***
1983_Pesticide Regulation	-0.0113	(0.0365)	
σ^2	0.0346	(0.0025)	***
λ	0.8236	(0.0216)	***
Expected Mean Efficiency	0.9247		

Source: Author's Calculations
Significance codes 0 :'***'0.001 :'**' 0.01 :'*' 0.05 :'.' 0.1 :' '

Assuming that inefficiency is influenced by some observable environmental variables (*Zs*), we consider the error effect model initially developed by Kumbhakar, Ghosh and McGuckin (1991) and generalized later by Battese and Coelli (1995). *Zs* variables consist of the creation EPA and the introduction of two pieces of pesticide regulation: the 1972 DDT ban and the 1983 toxaphene ban.

Table 5 reveals that inefficiency amounts to 40.4% of the total variance and the remaining 60% is due to random variation given an estimated lambda of 0.8236. The *z*-test rejects the null hypothesis of no differences in inefficiency among states; the variance σ_u^2 being significantly greater than 0. Alternatively, the performed likelihood ratio test positing a null-hypothesis of no difference in efficiency across states as in OLS, versus the alternative of difference as in

SFA, strongly rejects the null hypothesis($LR_{\chi=327.06\ ,df=4}$ and $P - \text{value} = 0.000$) and corroborates the z-test conclusion. The expected mean efficiency is equal to 0.9247 suggesting that on average the desirable output could have been expanded by 8.1% (1/0.9247-1) and inputs and water pollution could have been contracted by 7.5% (1-0.9247). The EPA's inception and its banning use of DDT and toxaphene suggest an improvement in efficiency associated with the regulation.

While the minimum distance computation offers the benefits of providing estimates consistent with monotonicity and to a large extent with convexity, its statistical inference relies on a more involved bootstrapping approach beyond the scope of this study. In fact, Andrew (2000) shows that if parameters are at the boundary of the feasible space, the standard bootstrapping technique provides an inconsistent covariance matrix. Alternatively, the Bayesian approach suggested by O'Donnel and Coelli(2005) is to be considered to impose these regularity conditions and preserve all the benefit provided by a translog parametric estimation(statistical inference included). But here, our interpretation is limited to the third column of table 4, the restricted-adjusted estimates. The time trend, proxy for technical change, shows a technical progress of 0.5% at an increasing rate over the considered period. Estimate for the desirable outputs, recovered from equation (12) suggests a technological bias towards more production desirable outputs than water pollution mitigation. Among undesirable outputs, the innovation is biased towards a reduction of risk to human health from pesticide leaching and runoff compared to the risk to aquatic life from pesticide leaching. In nutshell, innovation in the US agriculture has reduced water pollution impacting human health more than aquatic life. On the input side, technical progress is capital, land and labor saving and intermediate inputs using.

To calculate the Malmquist Productivity index in equation (20), we assume constant return to scale. The resulting productivity index reveals a 0.8% annual growth rate (table 8). Results from nonparametric setting by Ball et al. (2004) suggest an environmentally sensitive productivity growth of 0.98% and a decline in growth rate to 0.54% per year in the environmental productivity index. Further results show that productivity in US agriculture is mainly driven by technical change with a 0.51% annual growth rate. This result falls out of the range of 1.25 and 1.92 % change from recent studies that ignore environmental impacts (Fulginiti, 2010 and O'Donnell, 2012).

Additional information from the translog output distance function estimation consists of inputs substitutability or complementarity, and the degree of complementariness between desirable and undesirable outputs. The second terms-order cross terms between inputs α_{nl} can be interpreted as seconder-order(bias) measures of their effect on the desirable output specified as dependent variable.

$$B_{nl} = \frac{\partial S_k}{\partial lnx_l} = S_n.(\epsilon_{nl} - \epsilon_{ml}) = \epsilon_{m,n}.(\epsilon_{nl} - \epsilon_{ml}) = \frac{\partial \epsilon_{n,l}}{\partial lnx_l} = \alpha_{nl} \qquad (27)$$

where $S_n = \partial lny / \partial lnx_k$ is the cost share of input x_n, here referred to as implicit share, corresponding to its proportional marginal product.

Morrison-Paul *et al*.(2000) define the bias B_{nl} as a share weighted relative version of the marginal product elasticity $\epsilon_{nl} = \partial ln / \partial lnx_l$ which characterizes substitutability such that an increase in x_l will be associated with an expansion in production but also in more increase productivity of complement inputs than substitutes. From (27) the complete expression characterizing the full share elasticity $\epsilon_{m,n}$ corresponding to this effect is: $C_{n,l} = B_{n,l}.lnx_l = \alpha_{nl}.lnx_l$.

Consistent with a negative dependent variable in equation (14) a negative (positive) $C_{n,l}$ reflects the expansion (reduction) in production and suggests complementarity (substitutability) of inputs x_n and x_l .

Table 6 Desirable output elasticity and Second-Order Terms

	Capital	***Land***	***Labor***	***InterInput***
$\boldsymbol{\epsilon_{y,x_n}}$	-0.1040	-0.0112	-0.3561	-0.0051
$\boldsymbol{C_{n,Capital}}$	0.0185	0.0040	0.0181	0.0073
$\boldsymbol{C_{n,Land}}$	0.0035	0.0015	-0.0020	0.0008
$\boldsymbol{C_{n,Labor}}$	0.0118	-0.0015	-0.0134	0.0021
$\boldsymbol{C_{n,IntInput}}$	-0.1028	-0.0040	-0.0134	-0.0087

Source: Author's Calculations

Substuatibility prevails for most inputs combinations expect for labor and land which are complementary (table 6).

Following Grosskpof, Margaritas, and Valdmanis (1995) and Cuesta, Lovell and Zofio (2009) the marginal rate of transformation between desirable and undesirable outputs along the production possibility frontier can defined as:

$$(28) \quad MRT_{y,b} = \left(\frac{\partial D_E(x,y,b)}{\partial y} / \frac{\partial D_E(x,y,b)}{\partial b^*}\right) = \left(\frac{\partial lnD_E(x,y,b)}{\partial lny} / \frac{\partial D_E(x,y,b)}{\partial lnb^*}\right). (b^*/y)$$

$$= (\epsilon_y/\epsilon_b) * (b^*/y)$$

shows that the ratio of the elasticities is subject to the variation as long as the ratio of outputs varies. In light of Grosskpof, Margaritas, and Valdmanis(1995), Cuesta normalize MRT (28) by the output ratio to obtain a measure of relative opportunity cost referred to as marginal rate of transformation relative to the output mix.

Table 7. Desirable($\mathbf{y}$) and undesirable ($\mathbf{b}$)outputs Substitutability: $\mathbf{Sub_{y,b}}$ (1960-1997)

$Sub_{y,b1}$	$Sub_{y,b2}$	$Sub_{y,b3}$	ϵ_y	ϵ_{b1}	ϵ_{b2}	ϵ_{b3}
1.41E+15	4.30E+01	6.10E+17	0.4937	6.9E-16	-2.3E-02	-1.60E-18

Source : Author's calculation
b_1 : index of risk to human health from exposure to pesticide leaching;
b_2 : index of risk to aquatic life from exposure to pesticide runoff
b_3 : index of risk to aquatic life from exposure to pesticide leaching

$$(39) \quad Sub_{y,b} = (\epsilon_y/\epsilon_b)$$

The higher opportunity cost of desirable output in terms of undesirable outputs (relative complementarity) is characterized by a greater absolute value of $Sub_{y,b}$. ϵ_y is recovered from the almost homogeneity constraint (12). Results from table 7 reveal higher relative complementarity for output production and water pollution from pesticide leaching ($Sub_{y,b1}, Sub_{y,b3}$) . In other words, the opportunity cost of desirable output (livestock and crops) is higher relative to pollution from pesticide leaching than from runoff.

Table 8. US States Annual Total Factor Productivity Change, Efficiency Change and Technical Change (1960-1997)

STATES	TFP	TC	EC	STATES	TFP	TC	EC
AL	1.0096	1.0055	1.0041	NC	1.0082	1.0049	1.0033
AR	1.0150	1.0063	1.0086	ND	1.0071	1.0046	1.0025
AZ	1.0094	1.0058	1.0035	NE	1.0106	1.0049	1.0057
CA	1.0100	1.0056	1.0044	NH	1.0091	1.0064	1.0027
CO	1.0079	1.0055	1.0024	NJ	1.0067	1.0051	1.0016
CT	1.0072	1.0049	1.0024	NM	1.0087	1.0046	1.0041
DE	1.0094	1.0072	1.0022	NV	1.0069	1.0061	1.0009
FL	1.0118	1.0058	1.0060	NY	1.0093	1.0054	1.0039
GA	1.0076	1.0055	1.0020	OH	1.0059	1.0040	1.0019
IA	1.0056	1.0045	1.0011	OK	1.0100	1.0050	1.0050
ID	1.0071	1.0050	1.0021	OR	1.0058	1.0052	1.0007
IL	1.0084	1.0049	1.0034	PA	1.0070	1.0046	1.0023
IN	1.0064	1.0042	1.0022	RI	1.0076	1.0059	1.0016
KS	1.0075	1.0048	1.0027	SC	1.0100	1.0047	1.0053
KY	1.0078	1.0043	1.0035	SD	1.0066	1.0047	1.0019
LA	1.0062	1.0046	1.0016	TN	1.0077	1.0045	1.0032
MA	1.0082	1.0059	1.0022	TX	1.0080	1.0046	1.0034
MD	1.0069	1.0051	1.0017	UT	1.0079	1.0056	1.0023
ME	1.0099	1.0049	1.0050	VA	1.0081	1.0050	1.0031
MI	1.0059	1.0043	1.0016	VT	1.0084	1.0048	1.0036
MN	1.0060	1.0046	1.0014	WA	1.0070	1.0051	1.0018
MO	1.0092	1.0050	1.0042	WI	1.0055	1.0041	1.0014
MS	1.0075	1.0045	1.0030	WV	1.0083	1.0054	1.0029
MT	1.0067	1.0046	1.0021	WY	1.0072	1.0055	1.0017
Geomean					**1.0080**	**1.0051**	**1.0029**

Source: Author's Calculation

4. Conclusion

To account for water pollution in US agricultural productivity, we estimate a translog hyperbolic output distance function for the 48 U.S. continental states using capital, land, intermediate inputs and labor as inputs in the joint production of crops, livestock and water pollution proxies. The estimated environmentally adjusted measure reveals a TFP growth rate of 0.8%. Technical progress turns to be biased to towards production of the desirable outputs and remains the main component of the TFP growth. This result is consistent with that the one from non-parametric environmentally sensitive indexes in Ball et al. (2004). One limitation of this study is its failure to allow statistical inference on the restricted and adjusted estimates. Such limitation can be overcome by considering a Bayesian approach.

APPENDIX 3

APPENDIX 3.1 ADDITIONAL OUTPUT TABLES

Table 9 Stochastic Frontier Estimates prior to imposing Monotonicity (equation 14)

Variables	Estimate	Std-Error	
Intercept	-0.2009	(0.1071)	.
IR_HPL	-0.0666	(0.0106)	***
IR_HPR	0.1013	(0.0232)	***
IR_APL	0.0176	(0.0079)	*
Capital	-0.1757	(0.0509)	***
Land	0.0494	(0.0308)	
Labor	-0.0134	(0.0286)	
InterInput	-0.4393	(0.0644)	***
Time	-0.0016	(0.0019)	
*IR_HPL*IR_HPL*	-0.0022	(0.0009)	*
*IR_HPL*IR_HPR*	0.0025	(0.0013)	.
*IR_HPL*IR_APL*	0.0002	(0.0005)	
*IR_HPL*Capital*	0.0253	(0.0042)	***
*IR_HPL*Land*	0.0010	(0.0019)	
*IR_HPL*Labor*	0.0074	(0.0018)	***
*IR_HPL*InterInput*	-0.0347	(0.0048)	***
*IR_HPL*Time*	0.0002	(0.0001)	.
*IR_HPR*IR_HPR*	-0.0139	(0.0030)	***
*IR_HPR*IR_APL*	-0.0003	(0.0009)	
*IR_HPR*Capital*	-0.0077	(0.0067)	
*IR_HPR*Land*	-0.0224	(0.0038)	***
*IR_HPR*Labor*	-0.0084	(0.0040)	*
*IR_HPR*InterInput*	0.0461	(0.0087)	***
*IR_HPR*Time*	0.0002	(0.0002)	
*IR_APL*IR_APL*	0.0000	(0.0005)	
*IR_APL*Capital*	-0.0076	(0.0021)	***
*IR_APL*Land*	-0.0009	(0.0013)	
*IR_APL*Labor*	-0.0028	(0.0010)	**
*IR_APL*InterInput*	0.0105	(0.0028)	***
*IR_APL*Time*	-0.0002	(0.0001)	.
*Capital*Capital*	0.0144	(0.0191)	
*Capital*Land*	0.0748	(0.0082)	***
*Capital*Labor*	0.0445	(0.0063)	***
*Capital*InterInput*	-0.1238	(0.0169)	***
			***

Source : Author's Estimations

Table 9 (Continued) Stochastic Frontier Estimates prior to imposing Monotonicity (equation 14)

Variables	Estimate	Std-Error	
*Capital*Time*	0.0023	(0.0005)	***
*Land*Land*	0.0467	(0.0081)	***
*Land*Labor*	-0.0074	(0.0038)	.
*Land*InterInput*	-0.0941	(0.0109)	***
*Land*Time*	0.0014	(0.0003)	***
*Labor*Labor*	0.0199	(0.0062)	**
*Labor*InterInput*	-0.0479	(0.0084)	***
*InterInput*Time*	0.0002	(0.0002)	
*InterInput*InterInput*	0.2238	(0.0182)	***
*InterInput*Time*	-0.0038	(0.0006)	***
*Time*Time*	-0.0003	(0.0000)	***
NE_Plains Dummy	0.0298	(0.0066)	***
Appalachian_Dummy	-0.0086	(0.0084)	
SE_Plains Dummy	0.1131	(0.0089)	***
Lake_States_Dummy	0.0540	(0.0075)	***
Cornbelt_ Dummy	0.0643	(0.0087)	***
Delta_ Dummy	0.0384	(0.0078)	***
Northern_Plains_Dummy	0.0684	(0.0103)	***
Southern_Plains Dummy	-0.0506	(0.0085)	***
Mountain_Dummy	-0.1069	(0.0082)	***
EPA_Inception	0.0199	(0.0177)	
1972_Pesticide Regulation	-0.0216	(0.0186)	
1983_Pesticide Regulation	0.0868	(0.0110)	***
σ^2	0.0060	(0.0006)	***
λ	0.7355	(0.0490)	***
Expected Mean Efficiency	0.9340		

Source: Author's Estimations
Significance codes 0 :'***' 0.001 :'**' 0.01 :'*' 0.05 :'.' 0.1 :' '

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