Incorporating "Bads" and "Goods" in the Measurement of Agricultural Productivity Growth in the U.S.

Nataliya Plesha

Department of Agriculture and Resource Economics, University of Connecticut

nataliya.plesha@uconn.edu

Subhash C. Ray

Department of Economics, University of Connecticut

subhash.ray@uconn.edu

Richard Nehring

Economic Research Service/United States Department of Agriculture

rnehring@ers.usda.gov

Eldon Ball

Economic Research Service/ United States Department of Agriculture

eball@ers.usda.gov

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Productive utilization of resources has enabled American agriculture to supply the nation with vast quantities of food at a high level of efficiency. A variety of factors have contributed to the impressive growth in the agricultural productivity over the last half century. A comparison of agricultural production patterns in the United States during the last 50 years shows relatively stable patterns of changes in land use at the national level side by side with larger unexpected shifts in land use at regional and State levels. For example, between 1960 and 2011 the annual acreage devoted to crop production (including cropland harvested) declined. At the same time, land on which crops failed and cultivated summer fallow – increased by 16 % in the Corn Belt and decreased by 15 % in the remaining regions (ERS/USDA, 2011). The share of agricultural labor in the total labor force steadily decreased in the last few decades. The number of people employed in agriculture also declined. However, it is widely accepted that enhanced agricultural growth and productivity are the major contributors to economic growth in U.S. agriculture (e.g., the aggregate input use measure implies a 0.11 percent annual increase while the level of U.S. farm output shows an average growth rate of 1.63 percent) (ERS/USDA, 2012). Technological change has resulted in more efficient and effective inputs or allowed inputs to be combined in new and better ways leading to increases in agricultural productivity (i.e., which can be obtained either by producing more output with the same amount of inputs or producing the same amount of output with a smaller amount of inputs). As noted by Huffman and Everson (1992) the major public sector investments in research and development led to technological change which was rapidly adopted by farmers. In fact, modern agriculture may suffer significant economic losses in yield and quality without intensive use of pesticides and other chemicals. It is estimated that about 700 million pounds of more than 600 different pesticide types are applied annually in the

United States at a cost of $10 billion (Pimentel and Greiner, 1997). Due to a rapid expansion of the ethanol industry total U.S. corn acreage increased 19 percent between 2006 and 2007 (i.e., Department of Agriculture estimates 90.5 million acres of corn were planted in 2007, an increase of 12.8 million acres from 2006). Even though prices paid for pesticides increased by an additional 9 percent in 2008 and continued to increase in 2009, estimates of pesticide expenditures fell by $900 million (7.8%) in 2010 due to lower prices and a decrease in crop production.

However, the USDA shows that 2011 pesticide expenses increased by about $100 million resulting from a slight increase of planted acres and a one-percent rise in prices paid. Some believe that increased food and fiber production has come at a cost to environmental quality.

Updated, revised and extended through 1997 USDA data on “goods” and “bads” enable us to present a comprehensive productivity analysis of the U.S. Agricultural Sector that spans across forty-eight states. The findings from this study are expected to differ from the previous results reported in Harper et al. “*New Developments in Productivity Analysis”* (2001). The results may be influenced by differential increases in use of low toxic pesticides (i.e., use of glyphosate across the states) due to increased awareness and attitudes amongst the farmers regarding the environmental issues and adoption of more stringent environmental regulation.

Crop Production, Total Factor Productivity Growth and the Environment, “Good’ and “Bad” Outputs

According to the USDA/Economic Research Service (2007) total factor productivity (TFP) statistical series, total factor productivity is an important indicator of the long run performance of the agricultural sector in the United States. It separates the effects of technological change and related factors from the effects of changes in the quantity of inputs on the growth of agricultural output. The statistical series show changes in total output (an aggregate measure of crop, livestock commodities and farm related services), total inputs (an aggregate measure of capital, land, labor, energy, agricultural chemicals such as pesticides and fertilizers, and other materials) and total factor productivity from 1960 to 2004. For aggregate output, the total agricultural production increased and aggregate input use in agriculture slightly decreased over the 1960-2004 period. While the use of some inputs such as pesticides, fertilizers and capital display growing patterns, these increases were more than offset by reductions in cropland and total labor force recorded as working in agriculture. In general, the amount of crop, livestock and the farm related output produced per unit of aggregate measure of input , as measured by TFP, increased from 1960 to 2004. The agricultural productivity growth was substantial in each decade, raising output while requiring little or no increase in inputs. The growth in TFP in agriculture saved natural resources, including land, and freed labor for employment absorbed by other sectors.

Over the last several decades, the long run productivity growth in the agriculture sector has been sustained. However, productivity indices fluctuate from year to year due to weather, change in policy interventions, general economic conditions, and other factors. In the short run, the inputs employed in agriculture are relatively fixed, so much of the annual fluctuations in output is attributable to annual fluctuations in measured productivity.

Governmental policies can have a dramatic effect on the rate of agricultural productivity growth in both the short run and the long run. A change in policy interventions may lead to a sharp increase or decrease in measured productivity (i.e., variation from one year to the next). Long run and short run fluctuations in productivity growth should be viewed separately. In the short run, fluctuations are evident but usually recover quickly within 1 or 2 years. The long run trend in productivity growth is most important when evaluating policy interventions in the agricultural sector in the long run. The most common policies are the macro-economic policies that support new investment and policies that support agricultural research and development in encouraging innovation and productivity gains in agriculture. Furthermore, both the public and private sectors continue to invest heavily in research to develop new cost-effective techniques for the farm sector.

Modern pest management utilizes a wider range of appropriate pest management options despite the diversity of chemical use in agriculture. Both insect and herbicide resistant varieties of chemicals are commonly used on corn and cotton production, while soybean farmers generally use different herbicides. A significant overall trend in recent years has been toward use of less-toxic or non-toxic active ingredients in pesticide products. In fact, we see many examples of a major change in premix products that control annual broadleaf and grass weeds in corn (e.g., from metholachlor to acetochlor). It is worth mentioning that the glyphosate is the most widely used herbicide in the United Sates, in part because of its low toxicity. At the same time, atrazine is used on up 85% of all corn crops even though its environmental risks outweigh its benefits.

In the United States, the Environmental Protection Agency (EPA) regulates pesticides. All pesticides used must be approved (licensed) by the EPA and must be periodically reregistered to ensure that they meet safety standards.

In recent decades, chemical control of agricultural pests has been highly influenced by technical/scientific advances and program policy factors. The most common factors include adoption of genetically engineered (GE) crops, corn-based ethanol production, as well as climate change, increased conservation tillage, crop rotation and fundamental modifications in government programs. Minimizing the amount of pesticides used on crops while tracking productivity and maintaining excellent yields in the U.S. agricultural sector is crucial in maintaining both food security and environmental quality.

Natural resource depletion and national income accounting, so-called green accounting, have become very popular as research topics, but relatively little attention has been accorded in the productivity literature to the specific role that environmental attributes play in conventional measures of economic performance and efficiency at the plant, firm or industry level. Conventional measures of productivity, technical efficiency and technical change are based on marketed outputs and inputs, but they ignore changes in by-products of a specific subset of polluting inputs or bad outputs. It is useful and informative to incorporate these two productivity variables, good and bad outputs, when measuring the efficiency or productivity change in agriculture. Our attention here is on progress in the agricultural sector and environmental impacts of agricultural production methods that may be recognized as the driving forces behind this progress. Ball et al. (1999), for example, find that measured productivity outcomes differ when undesirable outputs (i.e., proxy effects of pesticides and fertilizer on groundwater and surface-water quality for the 1972-1993 time period) are taken into account.

Over the last few decades several attempts have been made in the literature to identify the impacts of pollutant outputs in agricultural efficiency and productivity measures. Pittman (1983) provided the earliest attempt at incorporating undesirable or bad outputs in conventional efficiency measurements based on analysis of Wisconsin paper mills. He made adjustments to the Caves et al. (1982) multilateral productivity index and found the inclusion of undesirable outputs to be an important factor in substantial changes in the rank order of productivity outcome measures. Furthermore, Färe, Grosskopf, Lovell and Pasurka (1989) used the Pittman data and included a pollution variable as a bad output into a production model. In particular, this study applied the hyperbolic Data Envelopment Analysis (DEA) methods in the estimation process and introduced the application of the weak disposability concept to account for the fact that the firm cannot freely dispose of the undesirable outputs (pollution). In contrast to weak disposability (i.e., expensive disposal), strong disposability implies that unwanted inputs or outputs of technology are likely to be freely disposable at no cost. Several years later, Färe, Grosskopf, Lovell and Yaisawarng (1993) used parametric output distance functions to repeat the analysis that was designed to let them easily calculate underlying shadow prices of the undesirable outputs.

Different versions of similar approaches have subsequently been used in a number of applied studies with the application to other industries such as fossil-fuel fired-electric utilities or Belgian pig-finishing farms (e.g., Färe, Grosskopf and Tyteca, 1996; Chung, Färe and Grosskopf, 1997; Färe, Grosskopf and Pasurka, 2001; Coelli et al., 2005). Recently, Ball et al. (2001), Ball et al. (2002) and Asmilde and Hougaard (2004) studied the productivity growth of U.S. agriculture in the presence of desirable (good) and undesirable (bad) outputs exploiting the connection to the efficiency and productivity measurement literature and employed Data Envelopment Analysis (DEA) in the estimation process.

Some studies on measures of agricultural efficiency and productivity (e.g., Hailu and Veeman, 2001) provided a comparison analysis of conceptual framework and the empirical performance of alternative approaches. They explained the relative strengths and weaknesses of different alternative methods such as input distance functions, output distance functions, nonparamertric methods, and index number approaches using Canadian paper and pulp industry data. Their findings suggest that adjusting agricultural productivity measures for environmental effects would significantly improve the understanding of productivity change in agriculture.

Research Methodology

The Production Technology

Consider an industry producing *m* outputs from *n* inputs. A pair of input-output bundles (x, y) is deemed feasible if the output bundle y can be produced from the corresponding input bundle x. The set of all feasible input-output bundles constitutes the technology set

$$T = \{(x, y): y \text{ can be produced from } x\}.$$

One way to define the technology in terms of a transformation function $F(x, y)$ is

$$T = \{(x, y): F(x, y) \leq 1\}.$$

If $F(x, y)$ is differentiable, it is conventional to assume that $\frac{\partial F}{\partial x_i} \leq 0$ for each input i

and $\frac{\partial F}{\partial y_j} \geq 0$ for each output j. The first implies that if $F(x^0, y^0) \leq 1$ for some input-output combination (x^0, y^0) then an increase in any input without a corresponding decrease in another input would not render the output bundle y^0 infeasible. Similarly, if the quantity any one output is reduced without increasing any other output, x^0 would be able to produce the new output bundle. These are known as free disposability assumptions.

One may, however, avoid an explicit parametric specification of the transformation function and merely impose a number of fairly weak restrictions on the admissible technology. In particular, one assumes only that the technology set is convex and that both inputs and outputs are freely disposable. These assumptions can be formally stated as:

(i) $(x^0, y^0), (x^1, y^1) \in T \Rightarrow (\lambda x^0 + (1-\lambda)x^1, \lambda y^0 + (1-\lambda) y^1) \in T \mid 0 \le \lambda \le 1.$

(ii) $(x^0, y^0) \in T \Rightarrow (x^1, y^0) \in T \mid x^1 \ge x^0.$

(iii) $(x^0, y^0) \in T \Rightarrow (x^0, y^1) \in T \mid y^1 \le y^0.$

The nonparametric method of Data Envelopment Analysis (DEA) permits one to empirically construct and estimate of the technology set from a set of observed input-output bundles with the additionally recognition of the fact that any observed input-output bundle is undoubtedly feasible. Thus, if (x^j, y^j) is one of a sample of N observations, then $(x^j, y^j) \in T$ for $j = 1,2,\ldots,N$. A DEA estimate of the technology set underlying the data is

$$S = \left\{ (x, y) : x \ge \sum_{1}^{N} \lambda_j x^j ; y \le \sum_{1}^{N} \lambda_j y^j , \sum_{1}^{N} \lambda_j = 1; \lambda_j \ge 0; (j = 1, 2, ..., N) \right\}.$$

If, in addition to convexity and free disposability of inputs and outputs one also assumes constant returns to scale, the corresponding estimate of the technology becomes

$$S^C = \left\{ (x, y) : x \ge \sum_{1}^{N} \lambda_j x^j ; y \le \sum_{1}^{N} \lambda_j y^j , \lambda_j \ge 0; (j = 1, 2, ..., N) \right\}.$$

Weak Disposability

There are many realistic situations where the assumption of free (also known as strong) disposability of inputs and/or outputs may be inappropriate. This is especially true when the production process results in both good (or desirable) outputs and bad (or undesirable) outputs. A widely used example is one of electric power generation, where burning fossil fuels produces both electric energy (the good output) and smoke (bad output). In this case one cannot reduce smoke (the bad output) and still produce the same level of power (the good output) from the same input bundle. In fact, pollution reduction would require additional resources to be employed for abatement. It is possible to argue that the good and the bad outputs are weakly disposable in the sense that they can be reduced together. That is, the level of pollution can be lowered if power generation is reduced as well. This is the view popularized by Färe, Grosskopf, and their co-authors in measurement of efficiency in the presence of bad outputs. It should be noted that the good and the bad outputs are effectively treated as joint products. In fact, Färe et al. consider them to be *null joint* meaning that the bad output can be eliminated only if no good output is produced either. For a formal representation, partition the output vector as $y=(g,b)$ where *g* and *b* are sub-vectors of good and bad outputs. Weak disposability of outputs can be defined as

$$(g^0,b^0,x)\in T \Rightarrow (kg^0,kb^0,x^0)\Rightarrow T \mid 0\le k\le 1.$$

An alternative interpretation of production of the bad alongside the good output is that the bad output results from the use of some polluting inputs that are used for the production of the good output. To the extent that there is any substitution possibility between the polluting and the 'neutral' inputs, it would be possible to reduce the bad output without reducing the good output by changing the input mix. Partition the input vector as $x=(p,q)$ where *p* and *q* represent the sub-vectors of polluting and neutral inputs, respectively. In this case, the weak disposability assumption applies to *b* and *p* rather than to *g* and *b*. One can think of two sub-technologies:

$T^1=\left\{(p,q;g):F^1(p,q;g)\le 1\right\}$ and

$T^2=\left\{(p,b):F^2(p,b)\le 1\right\}$.

The strong disposability assumptions about inputs and outputs apply for T^1 but only weak disposability applies for T^2. More specifically,

$$(p,b) \in T^2 \Rightarrow (kp, kb) \in T^2 \mid 0 \le k \le 1.$$

Finally, the overall technology set is

$$T = \left\{ (p,q,b,g) : (p,q,g) \in T^1, (p,b) \in T^2 \right\}.$$

In this view taken in Forsund (1998, 2009), Murty and Russell (2010) and others, the bad outputs are by-products of a specific subset of polluting inputs and are technologically separable from the good outputs.

The corresponding DEA estimates of the CRS technologies would be:

$$S_1^C = \left\{ (x; g, b) : x \ge \sum_1^N \lambda_j x^j ; g = k\sum_1^N \lambda_j g^j , b = k\sum_1^N \lambda_j b^j ; 1 \ge k \ge 0; \lambda_j \ge 0; (j = 1, 2, ..., N) \right\}$$

and

$$S_2^C = \left\{ (p, q; g, b) : q \ge \sum_1^N \lambda_j q^j ; p = k\sum_1^N \lambda_j b^j , b = k\sum_1^N \lambda_j b^j ; g \le \sum_1^N \lambda_j g^j ;\ \ 1 \ge k \ge 0; \lambda_j \ge 0; (j = 1, 2, ..., N) \right\}$$

Measuring Efficiency with Bad Outputs

Measured efficiency in production depends on the criterion function and the assumptions about the technology. For the present study we consider three alternatives:

(a) input-oriented efficiency assuming weak disposability of the offending input and the bad output;

(b) output-oriented efficiency assuming weak disposability of the offending input and the bad output;

(c) the Nerlove-Luenberger Directional efficiency assuming weak disposability of the offending input and the bad output.

In all cases, the good output and the neutral inputs are assumed to be freely disposable.

The corresponding efficiency measures would be

$\theta^* = \min \theta : (\theta p, q; g, \theta b) \in S_2^C$ for case (a), where the value of the DEA score ϑ^* equal to one means efficiency (i.e., there is more room for reducing the bad output coupled with polluting or bad input) while a value less than one means inefficiency

$\frac{1}{\varphi^*}$ where $\varphi^* = \max \varphi : (p, q, \varphi g, b) \in S_2^C$ for case (b), where the value of the DEA score ϕ^* equal to one means efficiency (i.e., there is more room for expanding the good output) while a value less than one means inefficiency

$(1-\beta^*)$ where $\beta^* = \max \beta : \left((1-\beta) p, q; (1+\beta) g, (1-\beta) b\right) \in S_2^C$ for the case (c), where the value of the DEA score β^* equal to zero means efficiency (i.e., there is more room for reducing the bad output coupled with polluting or bad input along with expanding the good output) while a value greater than zero means inefficiency.

For the present paper, denoting the vector of agricultural outputs as *g*, the pollution measures (harmful to people and fish) as *b*. fertilizers and other agricultural chemicals as *F*, and the other inputs as *x*, the alternative DEA models can be formulated as follows:

Model 1 (input-oriented efficiency) **Min** θ **(1)**

$$\textbf{s.t.}\ \sum \lambda_j g^j \geq g^0$$

$$\sum \lambda_j b_j = \theta b_0$$

$$\sum \lambda_j F_j = \theta F_0$$

$$\sum \lambda_j x^j \leq x^0$$

$$\lambda_j \geq 0$$

Model 2 (output-oriented efficiency) **Max** ϕ **(2)**

$$\textbf{s.t.}\ \sum \lambda_j g^j \geq \phi g^0$$

$$\sum \lambda_j b_j = \theta b_0$$

$$\sum \lambda_j F_j = \theta F_0$$

$$\sum \lambda_j x^j \leq x^0$$

$$\theta \leq 1$$

$$\lambda_j \geq 0$$

Model 3 (the Nerlove-Luenberger Directional efficiency) **(3)**

$$\textbf{Max}\ \beta$$

$$\textbf{s.t.}\ \sum \lambda_j g^j \geq (1+\beta) g^0$$

$$\sum \lambda_j b_j = (1-\beta) b_0$$

$$\sum \lambda_j F_j = (1-\beta) F_0$$

$$\sum \lambda_j x^j \leq x^0$$

$$\beta \geq 0$$

$$\lambda_j \geq 0$$

Data

The analysis employs conventional and environmental data. The conventional data used to construct the productivity indexes are based on desirable outputs and inputs. These data are described in Ball et.al, 1999 in Harper et al. "*New Developments in Productivity Analysis",* 2001. The most recent version of data is updated, revised and extended through 1997 (www.ers.usda.gov/Data/AgProductivity/). It is a unique panel of state-level data set developed by the U.S. Department of Agriculture's (USDA's) Economic Research Service (ERS) in cooperation with the USDA's Natural Resources Conservation Center (NRCS). The inputs include services of capital, land, labor, energy, agricultural chemicals and other goods. The desirable ("good") outputs are crops, livestock and farm related output. The data are available for the forty-eight contiguous states over the period 1960-1997. Longitudinal indexes of outputs and inputs are constructed. An index of relative, real output and real input between two states is obtained by dividing the nominal output (alternatively, input) value ratio for the two states by corresponding output (relatively, input) price index. EKS multilateral price indexes are then constructed for 1996. The base year is 1996 because that is the year for which detailed price information is available. The corresponding quantity indexes for the other years are formed by chain-linking them to a base Alabama state in 1996.

The data for our measure of detrimental effects of pesticides (undesirable outputs – henceforth “bads”) are based on Kellogg, Nehring, and Grube (1998), Kellogg and Nehring (1997), and Kellogg, Nehring, Grube, Plotkin, et al. (1999). The measurement of risk is based on the extent to which the concentration of a specific pesticide exceeds a water quality threshold. The annual concentration at the bottom of the root zone and the edge of the field for 4,700 representative soils is estimated for each of 200 pesticides applied to twelve crops. Furthermore, these estimated concentrations are compared to water quality thresholds that represent non harmful levels for chronic exposure. The risk indicator is constructed using the concentration-threshold ratio upon the evidence that the concentration of a specific pesticide exceeds the threshold. This leads the bad outputs indicators to proxy changes over time and across states in the risk from pesticide exposure (Ball et al., 2004). These “bads” were intended to capture the effects of the agricultural use of chemical pesticides on groundwater and surface water quality. We use two indicators of pesticide “bads”. The first indicator includes separate indexes of pesticide leaching into groundwater and runoff into surface water. The second indicator of indexes of “bads” accounts for toxicity and, therefore environmental risk factors. Additionally, we have two types of risk: one that is associated with exposure to humans and other that is associated with exposure to fish. More precisely we have four indicators of pesticide “bads”. We have a leaching indicator for human and a leaching indicator for fish; and we have a runoff indicator for human and a runoff indicator for fish. Pesticide leaching and runoff series from Kellogg et al. (2000) are updated by using state level productivity account information on quality-adjusted quantities of pesticides and acres planted by crop for the 12 crops used in the Kellog et.al analysis. A more detailed discussion of the construction of these series is provided in Kellogg et al. (2002).

The data shown in Table 1 are confined to summary annual values of all thirteen variables, aggregated across forty eight states using land variable as the weight indicator. Figure 1 and Figure 2 depict trends in all variables aggregated across states. As seen in Figure 1, good outputs (i.e., livestock, crops, and farm related output) have grown at a faster rate than any purchased input. The labor force for U.S. agriculture declined dramatically and steadily over 1960 to 1994. As a result, we expect a conventional efficiency measures to exhibit increasing patterns at the aggregate level. At the same time, a lot of interstate variation can lead to downward effects of efficiency measures in some states.

In contrast with the relatively smooth pattern of change in the good outputs and the purchased inputs, the four undesirable (bad) outputs exhibit dissimilar patterns of trends (Figure 2). The indicators of human risk-adjusted from exposure to pesticide runoff and fish risk-adjusted from exposure to pesticide runoff show moderate early growth along with the early growth in the purchased inputs excluding the labor force input. However, while the purchased inputs show the same slow growing patterns over the study period, the environmental risk indicators from pesticide runoff begin to decline in the mid-1970s with a sharp increase in fish risk-adjusted from exposure to pesticide runoff indicator in 1990. The indicators of human risk-adjusted from exposure to pesticide leaching and fish risk-adjusted from exposure to pesticide leaching indicators show extremely rapid early growth until mid-1970s followed by slower rates of decline and some growth of human risk-adjusted from exposure to pesticide leaching in mid-1990s. Regardless of the divergent time paths, we have no expectation concerning the relationship between the conventional and broad efficiency measures neither at the aggregate level nor at the state level.

In our analysis we model the production of “good” and “bad” outputs, allowing the good output and the neutral inputs to be freely disposable, both conceptually and empirically using three alternative ways to measure the efficiency level.

Preliminary Results

We apply our methods to a unique conventional and environmental panel of state-level data on outputs and inputs that is updated, revised and extended through 1997. Although our results are preliminary, they suggest that the efficiency measures differ depending on how the bad outputs are taken into consideration. The indexes of undesirable (bad) outputs explicitly account for toxic chemical effects so that we can assess the risks to both humans and the environment. In our analysis we use risk-adjusted indexes for both pesticide runoff and leaching. To that end, we consider two types of risk: that associated with exposure to humans (i.e., human risk-adjusted effect of pesticide leaching and human risk-adjusted effect of pesticide runoff) and that associated with exposure to fish (i.e., fish risk-adjusted effect of pesticide leaching and fish-adjusted effect of pesticide runoff). In our analysis we also include three good outputs, five good inputs and one polluting input. The variables are used to calculate data envelopment analysis input, output and the Nerlove-Luenberger Directional efficiency scores with three different model specifications. The same set of outputs and inputs are included in all the models.

The results for the forty eight states with the three different model specifications are summarized in the different tables. The study reveals considerable variations in state-wise efficiency scores. To illustrate, Tables 2, 3 and 4 exhibit the averages of the overall efficiency scores over time. We present the average efficiency scores for corn, cotton and soybean states. One interesting pattern we observe is that if we look at the key corn-producing states (Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin) they show that, in general, there is more room for reducing the bad output (coupled with the polluting input or bad input such as agricultural chemicals in our data set) than for expanding the good outputs. Selected individual states in this group such as Michigan (in 1960-1970: θ^* = 0.9774, in 1970-1980: θ^* =0.9501, and in 1980-1990: θ^* =0.8397) Minnesota (in 1960-1970: θ^* = 0.9773, in 1970-1980: θ^* =0.9307, and in 1980-1990: θ^* =0.9894) and Missouri (in 1960-1970: θ^* = 0.9335, in 1970-1980: θ^* =0.8016, in 1980-1990: θ^* =0.5481, and in 1990-1997: θ^* =0.5509) have consistently performed inefficiently with respect to pollution abatement (column θ^* in Table 2). Among the cotton states (e.g., Alabama, Arizona, California, Georgia, Louisiana, Mississippi, New Mexico, North Carolina, Oklahoma, South Carolina, Texas, and Tennessee), six out of 12 states were found efficient over the entire period. Louisiana (in 1960-1970: θ^* =0.6357, ϕ^* = 1.1192, and β^* = 0.1265, respectively; in 1970-1980: θ^* =0.8867, ϕ^* = 1.0277, and β^* = 0.0095, respectively; in 1980-1990: θ^* =0.7908, ϕ^* = 1.0397, and β^* = 0.0217, respectively), Mississippi (in 1960-1970: θ^* =0.7799, ϕ^* = 1.0033, and β^* = 0.0071, respectively; in 1970-1980: θ^* =0.7433, ϕ^* = 1.0138, and β^* = 0.0023, respectively) and Tennessee (in 1960-1970: θ^* =0.7309, ϕ^* = 1.0624, and β^* = 0.0329, respectively; in 1970-1980: θ^* =0.5368, ϕ^* = 1.1557, and β^* = 0.1417, respectively; in 1980-1990: θ^* =0.4930, ϕ^* =

1.2137, and β^* = 0.2358, respectively, and in 1990-1997: θ^*=0.8258, ϕ^* = 1.0492, and β^* = 0.0404, respectively) showed significant levels of inefficiency in pollution abatement (Table 3). The soybean states are the corn states plus Arkansas, Maryland, and Virginia. The last three states do not show any significant inefficiency (Table 4).

To obtain a better understanding of the preliminary results, we examine pesticide runoff risk indicators for protection of drinking water patterns in corn, cotton, and in soybean producing states (Figure 3 – Figure 7). Ball et al., 2002 estimated that the use of pesticides in the production of corn, cotton and soybean accounted for approximately two- thirds of the total pounds of active ingredients applied to the field. The pesticides that caused much of the leaching and runoff in the early 1970s were alachlor, atrazine, aldrin, carbofuran, phroate, trifluralin, and propachlor. The EPA, the main pesticides regulation institution, cancelled all uses of aldrin in 1974. In 1982, restrictions were imposed on the application of trifluralin. Most uses of carbofuran were cancelled in the early 1990s (Ball et al., 2002). Insecticide use is very important in cotton production. The most commonly used, not environmentally friendly, pesticides were aldrin and EPN. However, their use was cancelled in 1974 and 1987 respectively, thereby decreasing the risk to human health in the years since then.

The efficiency measures coincide with the decreasing pattern of pesticide applications for corn producing states. Our findings provide more room for reducing the bad output, along with the polluting input which may help to keep the declining pattern over the years (Figure 5). While there is no evident downward trend for the application of pesticides in Iowa (Figure 7), it is still more environmentally feasible to reduce bad output than to expand the good output. The cotton producing states show consistency with the efficiency score measures. Louisiana (Figure 6), for example, showed significant levels of inefficiency in pollution abatement and increasing patterns in the pesticide runoff risk indicator for protection of drinking water (i.e., increasing pattern in risk to human health).

Concluding Remarks

This paper presents findings on the efficiency score measures with undesirable or bad outputs and the offending bad input (i.e., pesticides and fertilizers) for twelve key corn producing states, twelve key cotton producing states, and fifteen key soybean producing states using a unique panel of state-level data set for 1960-1997. Our preliminary findings indicate that the efficiency scores for corn, cotton, and soybean producing states are consistent with the pesticide risk indicators for protection of drinking water patterns discussed in Kellogg et al, 2002. In general, there is more room for reducing the bad output along with the polluting input (e.g., pesticide and fertilizer) than for expanding the good outputs (e.g., crops, livestock, and farm related output) in the major corn and soybean producing states. Only half of the 12 cotton producing states were found to be efficient over the entire period.

Our findings using the updated, revised and extended through 1997 USDA data on "goods" and "bads" differ from the previous results reported in Harper et al. "*New Developments in Productivity Analysis*" (2001) due to the different approach (i.e., measured efficiency scores) used in this study. In our future research we intend to conduct a study using the same approach (i.e., measuring productivity growth using the Malmquist-Luenberger productivity index) with updated, revised and extended through 2004 USDA data on "goods" and "bads".

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Figure 1. Trends in Marketed Outputs and Purchased inputs

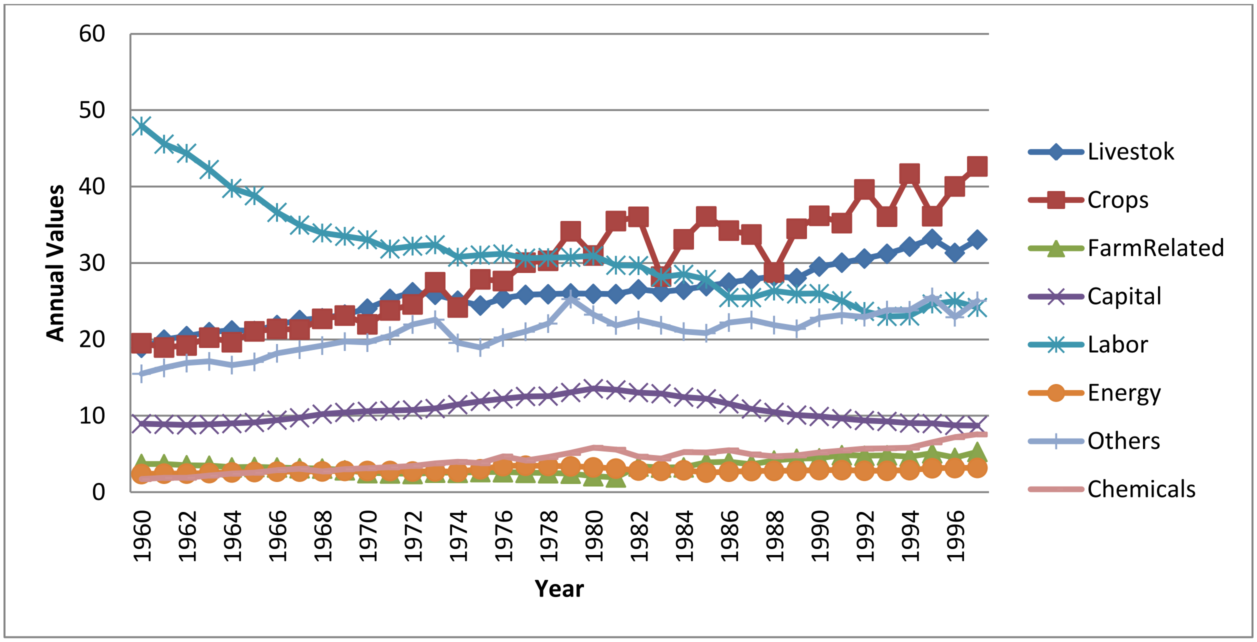


Figure 2. Trends in Environmental Impact Indicators

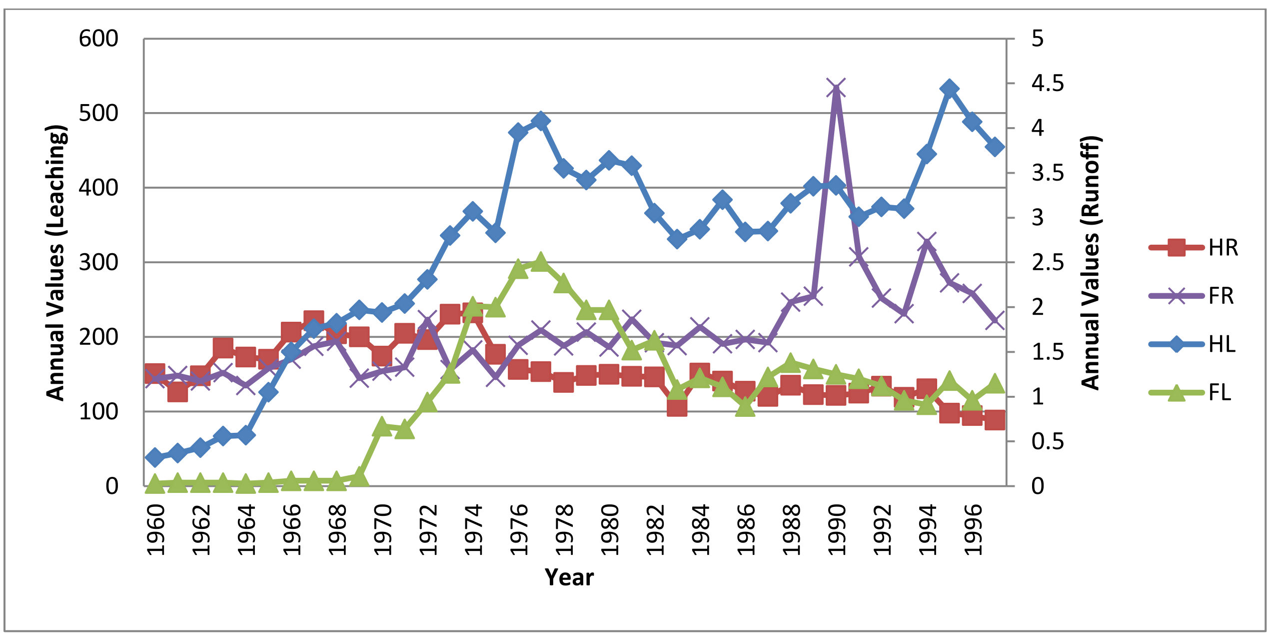
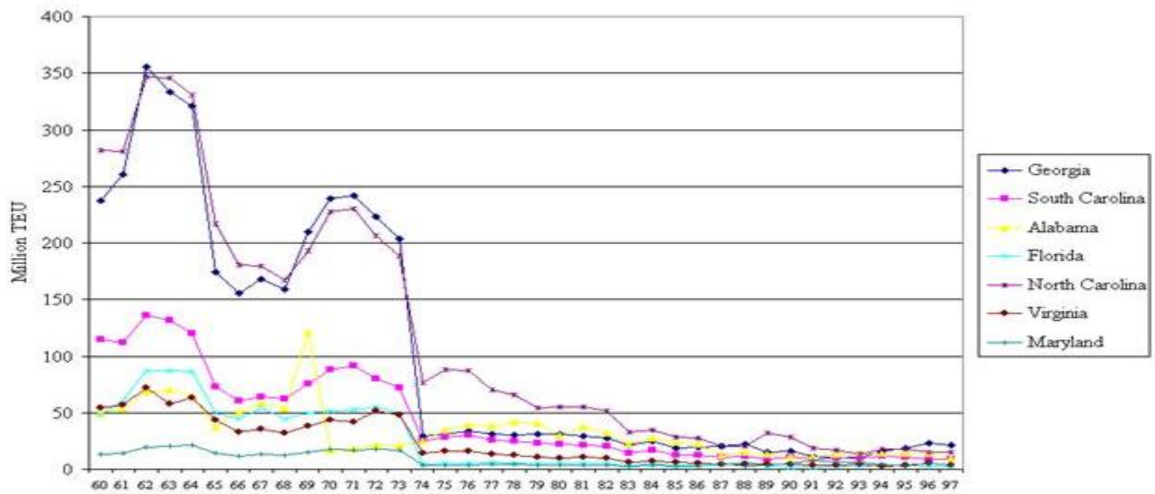
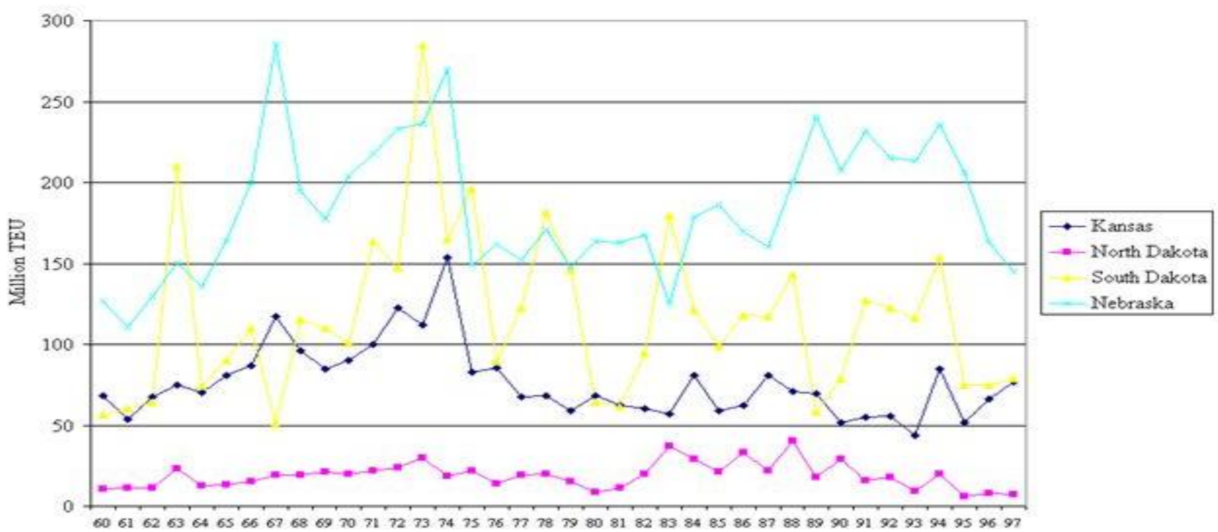


Figure 3. Pesticide Runoff Risk Indicators for Protection of Drinking Water, Southeast States



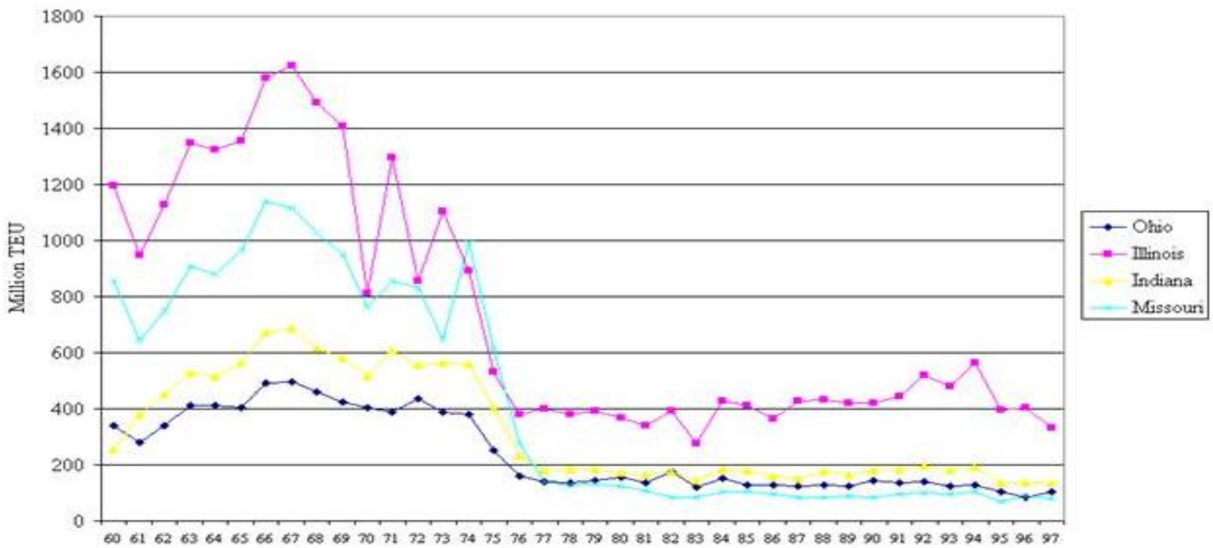
Source: Kellogg et al., 2000

Figure 4. Pesticide Runoff Risk Indicators for Protection of Drinking Water, Four Northern Plains States



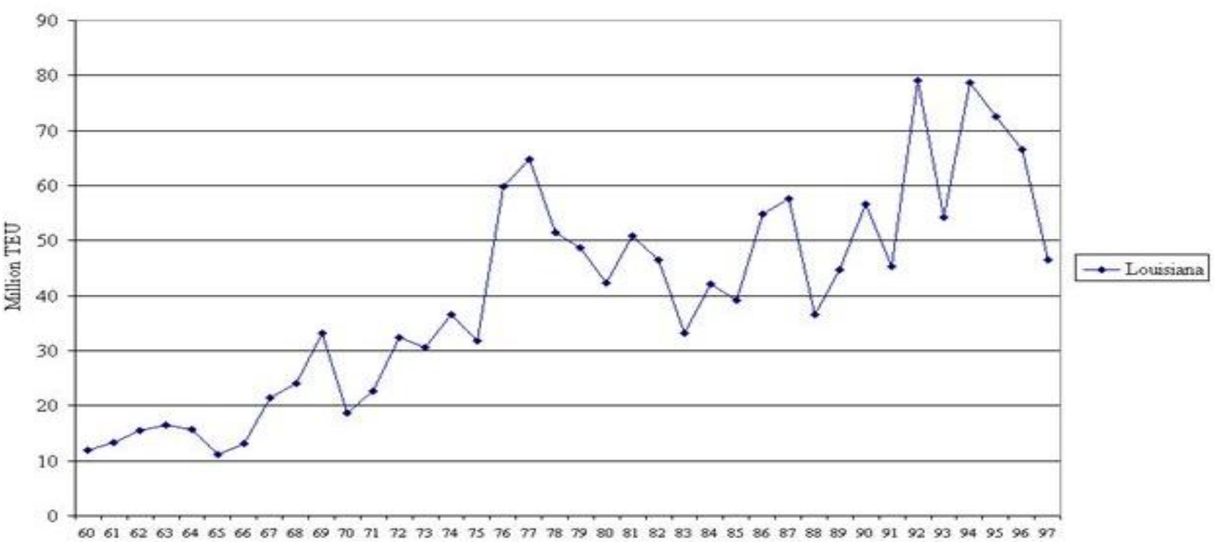
Source: Kellogg et al., 2000

Figure 5. Pesticide Runoff Risk Indicators for Protection of Drinking Water, Four Midwest States



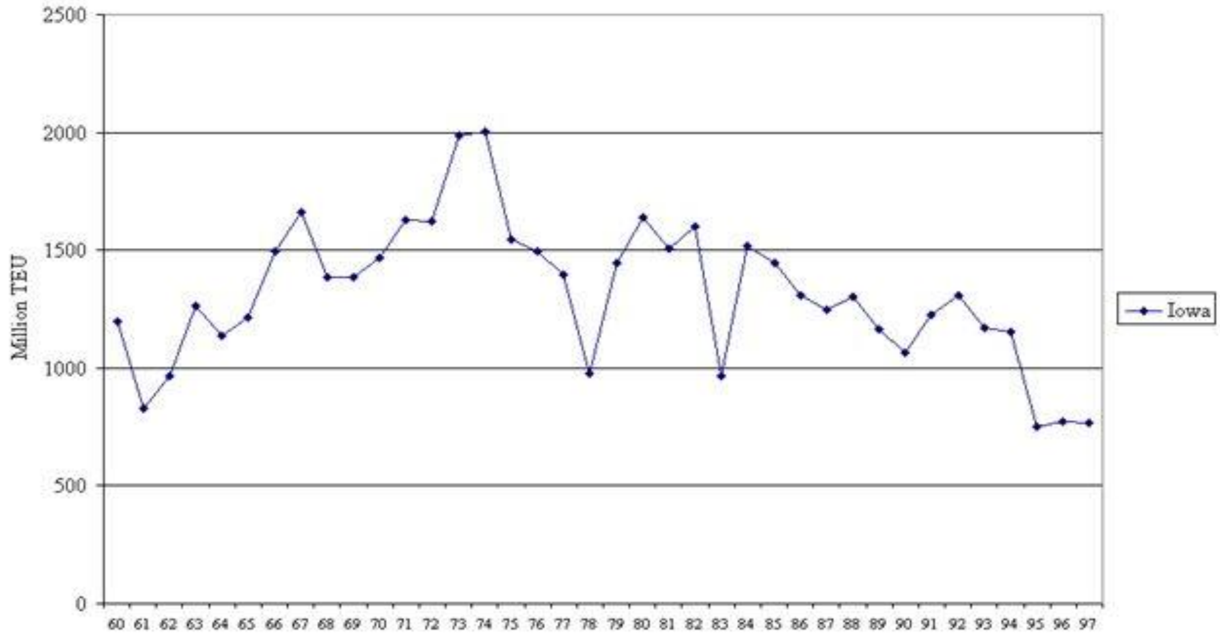
Source: Kellogg et al., 2000

Figure 6. Pesticide Runoff Risk Indicators for Protection of Drinking Water, Louisiana



Source: Kellogg et al., 2000

Figure 7. Pesticide Runoff Risk Indicators for Protection of Drinking Water, Iowa



Source: Kellogg et al., 2000

Table 1. Data Summary: Annual Values of the Thirteen Variables

Year	Livestock	Crops	Farm Related	Capital	Labor	Energy	Others	Agricultural Chemicals	HL	HR	FL	FR
1960	18.91	19.51	3.71	8.98	47.94	2.39	15.51	1.72	0.32	150.93	0.03	144.08
1961	19.98	18.95	3.68	8.89	45.57	2.44	16.28	1.88	0.37	126.35	0.04	148.33
1962	20.44	19.21	3.54	8.82	44.37	2.45	16.91	1.89	0.43	147.99	0.04	141.01
1963	20.96	20.24	3.48	8.87	42.24	2.52	17.13	2.18	0.56	185.13	0.04	152.18
1964	21.18	19.64	3.26	8.99	39.78	2.60	16.65	2.42	0.57	173.10	0.03	134.96
1965	21.11	21.06	3.31	9.14	38.82	2.65	17.07	2.55	1.05	170.15	0.04	158.05
1966	21.89	21.38	3.25	9.44	36.63	2.70	18.19	2.90	1.50	206.53	0.06	170.26
1967	22.54	21.30	3.15	9.75	34.97	2.71	18.67	3.08	1.76	221.82	0.06	187.49
1968	22.78	22.70	3.11	10.22	33.94	2.73	19.20	2.73	1.82	204.30	0.06	194.16
1969	23.26	23.13	2.88	10.45	33.51	2.80	19.72	3.01	1.97	200.17	0.11	144.81
1970	24.04	21.98	2.51	10.59	33.06	2.79	19.59	3.14	1.94	174.36	0.67	154.20
1971	25.32	23.80	2.47	10.70	31.85	2.79	20.50	3.26	2.04	204.91	0.64	159.53
1972	26.18	24.59	2.40	10.79	32.22	2.72	21.96	3.45	2.31	196.50	0.94	223.26
1973	25.85	27.49	2.57	10.96	32.39	2.73	22.59	3.78	2.80	230.56	1.26	156.32
1974	25.08	24.19	2.55	11.47	30.78	2.67	19.55	3.97	3.07	232.36	2.01	182.67
1975	24.44	27.87	2.65	11.90	31.05	3.01	18.95	3.80	2.83	176.79	2.00	145.91
1976	25.39	27.65	2.63	12.22	31.19	3.43	20.26	4.69	3.95	156.49	2.43	188.83
1977	25.84	30.06	2.55	12.54	30.64	3.48	21.02	4.16	4.08	153.58	2.51	209.31
1978	25.92	30.30	2.50	12.59	30.72	3.46	22.08	4.59	3.55	139.09	2.27	188.00
1979	26.03	34.16	2.44	13.06	30.75	3.39	25.29	5.14	3.42	148.43	1.97	206.50
1980	25.96	30.99	2.11	13.56	30.94	3.26	23.25	5.83	3.64	149.99	1.97	186.52
1981	25.94	35.50	1.95	13.40	29.72	3.10	21.84	5.58	3.58	147.28	1.52	223.73
1982	26.56	36.05	3.38	13.05	29.66	2.85	22.53	4.67	3.05	146.47	1.63	192.28
1983	26.23	28.23	3.24	12.90	28.15	2.80	21.86	4.41	2.76	106.94	1.08	188.39
1984	26.50	33.11	3.26	12.45	28.52	2.88	21.03	5.26	2.87	151.64	1.21	213.61
1985	26.98	36.10	3.92	12.23	27.87	2.58	20.82	5.19	3.20	140.86	1.11	190.87
1986	27.45	34.25	3.99	11.58	25.48	2.70	22.22	5.49	2.84	127.32	0.89	196.72
1987	27.84	33.74	3.66	10.91	25.48	2.78	22.55	4.96	2.85	120.39	1.22	192.42
1988	28.24	28.76	4.16	10.46	26.33	2.80	21.88	4.70	3.16	135.31	1.38	246.73
1989	28.02	34.49	4.39	10.11	25.96	2.80	21.40	4.82	3.35	122.72	1.31	254.72
1990	29.54	36.19	4.45	9.92	26.00	2.91	22.84	5.21	3.36	121.71	1.25	534.39
1991	30.05	35.23	4.86	9.63	25.07	2.90	23.21	5.47	3.01	124.75	1.20	307.41
1992	30.59	39.64	4.78	9.40	23.68	2.82	22.92	5.69	3.12	134.03	1.12	252.18
1993	31.21	36.08	4.84	9.27	23.02	2.81	23.85	5.76	3.10	119.11	0.96	231.19
1994	32.15	41.71	4.67	9.06	23.07	2.90	23.82	5.83	3.71	130.58	0.91	327.97
1995	33.17	36.13	5.10	8.99	24.64	3.15	25.57	6.53	4.44	97.92	1.18	272.53
1996	31.33	40.03	4.51	8.76	24.99	3.17	22.91	7.21	4.07	94.70	0.96	258.36
1997	33.07	42.65	5.29	8.73	24.18	3.19	25.06	7.57	3.79	88.64	1.15	222.24

Definitions of environmental impact indicators: HL – human risk-adjusted effects from exposure to pesticide leaching; HR – human risk-adjusted effects from exposure to pesticide runoff; Fl – fish risk-adjusted effect from exposure to pesticide leaching; and FR – fish risk-adjusted effect from exposure to pesticide runoff

Table 2. Efficiency Measures (θ^*, ϕ^* and β^*) for Corn Sates

Corn States	θ^*	ϕ^*	β^*
Illinois			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Indiana			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	0.8506	1	0
1990-1997	1	1	0
Iowa			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Kansas			
1960-1970	1	1	0
1970-1980	1	1	0.0146
1980-1990	0.8557	1.0548	0.0656
1990-1997	0.9451	1.0123	0.0197
Michigan			
1960-1970	0.9774	1	0.0171
1970-1980	0.9501	1.0160	0.0396
1980-1990	0.8397	1.0315	0.0328
1990-1997	1	1	0
Minnesota			
1960-1970	0.9773	1	0.0038
1970-1980	0.9307	1	0.0038
1980-1990	0.9894	1	0
1990-1997	1	1	0

Missouri			
1960-1970	0.9335	1.0231	0
1970-1980	0.8016	1.0660	0.0707
1980-1990	0.5481	1.1457	0.1557
1990-1997	0.5509	1.2103	0.2134
Nebraska			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	0.9890	1.0007	0.0042
1990-1997	1	1	0
North Dakota			
1960-1970	1	1	0.0001
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Ohio			
1960-1970	1	1	0
1970-1980	1	1	0.0063
1980-1990	1	1	0
1990-1997	1	1	0
South Dakota			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Wisconsin			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0

Table 3. Efficiency Measures (θ^*, ϕ^* and β^*) for Cotton Sates

Cotton States	θ^*	ϕ^*	β^*
Alabama			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Arizona			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
California			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Georgia			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Louisiana			
1960-1970	0.6357	1.1192	0.1265
1970-1980	0.8667	1.0277	0.0095
1980-1990	0.7908	1.0397	0.0217
1990-1997	1	1	0
Mississippi			
1960-1970	0.7799	1.0033	0.0071
1970-1980	0.7433	1.0138	0.0023
1980-1990	0.7572	1.0154	0
1990-1997	1	1	0

New Mexico			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
North Carolina			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Oklahoma			
1960-1970	0.9604	1.0077	0
1970-1980	0.8938	1.0084	0.0215
1980-1990	0.9501	1	0
1990-1997	0.9035	1	0.0107
South Carolina			
1960-1970	1	1	0
1970-1980	0.9656	1.0322	0.0216
1980-1990	0.7669	1.0454	0.0517
1990-1997	0.8806	1.0115	0.0117
Texas			
1960-1970	1	1	0
1970-1980	0.9243	1.0227	0.0513
1980-1990	0.9719	1	0.0089
1990-1997	1	1	0.0025
Tennessee			
1960-1970	0.7309	1.0624	0.0329
1970-1980	0.5368	1.1557	0.1417
1980-1990	0.4930	1.2137	0.2358
1990-1997	0.8258	1.0492	0.0404

Table 4. Efficiency Measures (θ^*, ϕ^* and β^*) for Soybean Sates

Soybean States	θ^*	ϕ^*	β^*
Arkansas			
1960-1970	0.9908	1.0025	0.0023
1970-1980	0.9908	1	0
1980-1990	0.9841	1.0005	0.0007
1990-1997	1	1	0
Illinois			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Indiana			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	0.8506	1	0
1990-1997	1	1	0
Iowa			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Kansas			
1960-1970	1	1	0
1970-1980	1	1	0.0146
1980-1990	0.8557	1.0548	0.0656
1990-1997	0.9451	1.0123	0.0197
Maryland			
1960-1970	0.9430	1.0078	0.0068
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0

Michigan			
1960-1970	0.9774	1	0.0171
1970-1980	0.9501	1.0160	0.0396
1980-1990	0.8397	1.0315	0.0328
1990-1997	1	1	0
Minnesota			
1960-1970	0.9773	1	0.0038
1970-1980	0.9307	1	0.0038
1980-1990	0.9894	1	0
1990-1997	1	1	0
Missouri			
1960-1970	0.9335	1.0231	0
1970-1980	0.8016	1.0660	0.0707
1980-1990	0.5481	1.1457	0.1557
1990-1997	0.5509	1.2103	0.2134
Nebraska			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	0.9890	1.0007	0.0042
1990-1997	1	1	0
North Dakota			
1960-1970	1	1	0.0001
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Ohio			
1960-1970	1	1	0
1970-1980	1	1	0.0063
1980-1990	1	1	0
1990-1997	1	1	0

South Dakota			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0
Virginia			
1960-1970	1	1	0
1970-1980	0.8887	1.0291	0.0283
1980-1990	1	1	0
1990-1997	0.9579	1.0115	0.0121
Wisconsin			
1960-1970	1	1	0
1970-1980	1	1	0
1980-1990	1	1	0
1990-1997	1	1	0