Shaping the USDA Agriculture Innovation Agenda: Addressing Agricultural Nonpoint Source Pollution from A Point Source Perspective

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Agrochemicals are crucial for modern agriculture, but improper use can cause nonpoint source pollution (NPS), harming water quality and health. Despite recognizing agriculture as a major NPS contributor, policies lag in addressing it. Current literature identifies three main approaches to mitigate NPS: voluntary programs, economic incentives, and command and control regulations, but lacks empirical studies. This paper introduces a production efficiency model inspired by the input-based Best Management Practices (BMPs) to tackle agrochemical overuse without affecting yields. It aims to address NPS by providing empirical estimates to guide evidence-based sustainable farming policies.

JEL: C61, Q15, Q18, Q53, D24

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I. Introduction

Chemical agents, formally known as agrochemicals, play a crucial role in modern agriculture by protecting and enhancing production. About a half million tons of pesticides, 12 million tons of nitrogen, and 4 million tons of phosphorus fertilizer

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are applied annually to crops in the continental United States (US EPA, 2023). USDA Economic Research Service also provides statistics that demonstrate the increasing importance of agrochemicals on U.S. farm operations. As reported by (Wang et al., 2024), "the estimates of quality-adjusted and unadjusted fertilizer quantities in 2019 were 2.5 times and 2 times (respectively) their 1948 level and 15 times and 8 times (respectively) for quality-adjusted and unadjusted pesticide quantities."

However, agrochemical products applied without consideration of the appropriate dosage, timing and method will lead to chemical runoff, resulting in nonpoint source pollution (NPS) that has deleterious effects on the environment and human health. For example, the American National Water Quality Assessment shows that agricultural runoff is the leading cause of water quality impacts on rivers and streams, the third leading source for lakes, and the second largest source of impairments to wetlands (US EPA, 2023).

Nitrate, a compound found in fertilizer, can easily enter drinking water in agricultural areas. A 2010 report on nutrients in ground and surface water by the U.S. Geological Survey found that nitrates were too high in 64 percent of shallow monitoring wells in agricultural and urban areas (US EPA, 2013). Once taken into the body, nitrates are converted into nitrites and high levels of nitrite in drinking water can cause methemoglobinemia or "blue baby syndrome". Infants under six months who drink water with high levels of nitrate can become seriously ill and die (US EPA, 2024).

Phosphorus is another type of nutrient for soil fertility and crop nutrition, commonly present in fertilizers. When runoff from landscapes carries phosphorus into lakes and streams, it can trigger harmful algae blooms that deplete oxygen in the water, leading to "dead zones" in aquatic ecosystems (O'Brien, 2015).

II. Literature Review

Agriculture is the leading contributor to nonpoint source pollution in waterways (Dowd et al., 2008), yet policymakers have responded slowly and ineffectively. Unlike point source pollution, nonpoint source pollution often discharges in pulses and is challenging to attribute to specific polluters. Given the complexities of identifying and monitoring nonpoint source pollution, current literature emphasizes the need for effective policy instruments to mitigate NPS, from the perspective of a government regulator.

As summarized by the literature survey (Dowd et al., 2008), there are three primary policy instruments for mitigating NPS: voluntary measures, economic incentives, and command and control regulations.

The voluntary approach, which aims to enhance environmental quality without mandatory participation, is often the preferred option for both polluters and regulators. (Alberini & Segerson, 2002; Lyon & Maxwell, 2002; Segerson & Walker, 2002) have grouped voluntary environmental programs into three types: unilateral action, negotiated agreement, and voluntary government program.

Economic incentives approach is the most cost-effective method to mitigate the harmful effects of pollution, as advocated by many economists. In various parts of the United States, an additional fee on agrochemicals—whether through a lump-sum or per-unit tax—has been implemented primarily to fund pollution control programs rather than to limit the use of polluting inputs. For instance, California has introduced a sales tax of 2.1 cents per dollar on agrochemicals to generate funds for producer training initiatives (California Department of Pesticide Regulation, 2024).

The concepts of ambient tax and subsidy have been introduced in the literature following the seminal paper "Uncertainty and Incentives for Nonpoint Pollution Control" (Segerson, 1988), which offers a theoretical framework for managing nonpoint source pollution by monitoring ambient pollutant concentrations. Recent experimental studies, including those by (Reichhuber et al., 2009), have tested this theory through laboratory and field experiments. Under this mechanism, the government provides targeted subsidies to farmers when observed pollution levels fall below a specified threshold, while imposing penalties if pollution exceeds that threshold. An ambient tax can be more effective than traditional input regulation and monitoring, provided that ambient concentrations can be measured at a lower cost and with acceptable accuracy. However, ambient concentrations can fluctuate significantly due to weather and other unpredictable events, potentially leading to unfair treatment of farmers who are genuinely trying to reduce pollution. For instance, if upstream farmers increase their discharges, the efforts of downstream farmers to lower their emissions may go unrecognized (Shortle et al., 1998).

The Command and Control (CAC) approach involves the government setting environmental quality standards and imposing penalties for non-compliance. While there is extensive literature on regulating point source pollution, there is limited research on the application of CAC policies to mitigate agricultural non-point source pollution. Generally, CAC policies can be categorized into design standards, which dictate how polluters manage their operations, and performance standards, which regulate total emissions. According to (Wu & Babcock, 1999), design standards are the most commonly used method to address agricultural pollution, while performance standards are gradually gaining attention, as reflected by the Mineral Accounting System (MINAS) in the Netherlands and Best Management Practice (BMPs) in the United States.

MINAS exemplifies a performance standard that employs economic incentives to encourage compliance. It follows a "farm-gate balanced approach" (van den Brandt & Smit, 1998) to track the total nitrogen and phosphorus inputs and outputs of individual farms. The difference between inputs and outputs represents the farm surplus, which is assumed to be lost to the environment. This surplus is then compared to an environmentally safe standard, and farmers incur a per-kilogram tax penalty for excessive discharges (Ondersteijn et al., 2002). However, MINAS has been deemed a failure due to implementation challenges across various farm types, particularly in poultry farms (OECD, 2005).

The United States has adopted a similar performance- and input-based approach to address NPS, under the umbrella term Best Management Practices (BMPs). The goal is to encourage farmers, in collaboration with university extension programs and farm service agencies, to implement cost-effective and appealing farming methods tailored to individual farms. According to the USDA Agricultural Research Service, a single practice rarely resolves pollution issues; instead, a combination of measures is often necessary. Each farm operator must determine the most suitable combination of BMPs based on specific soil types, climate conditions, and management practices. However, the implementation costs for certain BMPs, such as structural measures like manure storage systems, can be quite high (Sharpley et al., 2006). As a result, farmers may have financial incentives to choose and implement inappropriate or poorly designed BMPs, which may not yield measurable improvements in environmental performance.

(Sharpley et al., 2006) provides a comprehensive report on BMPs aimed at minimizing the negative impacts of phosphorus (P) on water quality in agricultural production systems. A key method within source BMPs is to prevent the accumulation of P in the soil beyond levels necessary for optimal crop growth by regulating P at the farmgate, particularly through effective fertilizer management. Efficient fertilizer management relies on regular soil testing, selecting appropriate nutrient application rates to meet realistic crop yield expectations, and applying commercial fertilizers using recommended methods that enhance nutrient availability to growing crops (Havlin et al., 2013). By carefully choosing the rate, method, and timing of P applications, farmers can significantly reduce the potential for P loss in runoff, thereby mitigating nonpoint source pollution.

III. Contribution

The literature on agricultural nonpoint source (NPS) pollution is relatively limited and primarily consists of analytical models. Given the scarcity of empirical studies in this area, a new approach that can provide quantifiable information would greatly benefit practitioners, especially in an era that emphasizes evidence-based policymaking for the public good.

To fill a large gap in the literature, the biggest contribution of this project is to offer fresh insights into agricultural NPS, particularly from a point source perspective. Building upon the input-based Best Management Practices approach, we propose a two-stage production efficiency model that can offer quantitative estimates to inform policy formulation and educational training for extension programs.

By utilizing micro-level farm production data collected through nationwide surveys conducted by the USDA National Agricultural Statistics Service, we can estimate the amount of agrochemicals that can be reduced on each farm without compromising yield. Unlike the traditional BMPs where farmers have financial incentives to choose poorly designed practices, farmers of all types (including commercial and hobby farmers) have financial incentives to reduce chemical usage to lower their operational costs. By tackling excessive agrochemical use and minimizing pollutant accumulation in the soil, we can decrease chemical runoff and the resulting diffuse water contamination, thereby reducing NPS.

IV. Estimation Method

The primary estimation method utilized in this study is the Data Envelopment Analysis (DEA), a nonparametric model used to evaluate the technical efficiency of one decision-making unit (DMU) compared to the production frontier (Charnes et al., 1978, 1981). It is the most powerful and useful methodology for the estimation of production functions and has been used extensively to supply new insights into activities (and entities) in a range of industries (Cooper et al., 2007). As explained in (Ray, 2004), DEA employs a linear programming method instead of the familiar least squares regression analysis that requires an explicit form of the production function and makes only a minimum number of assumptions about the underlying technology. Therefore, it produces no standard errors and leaves no room for hypothesis tests.

A range of DEA models have been developed that measure efficiency in different ways. These largely fall into the categories of being either input-oriented or output-oriented. Within input-oriented DEA, the linear programming model is configured to determine how much input use a firm could contract to achieve the same amount of output. Output-oriented DEA, on the other hand, is designed to determine a firm's potential output given its inputs if it operates efficiently. (Ray, 2004) points out that input- and output-oriented measures of technical efficiency of a firm will be different in most cases except for the case of constant returns to scale (CRS) when the average productivity at the projected reference points on the frontier is the same.

Since the primary objective of this paper is to reduce agricultural nonpoint source pollution by finding the optimal dosage of agrochemicals applied on each farm without comprising the yield, the traditional input-oriented DEA model using cross-sectional data will be the base (naïve) model and the input-oriented DEA model with fixed input constraints is the extension.

Considering the traditional input-oriented radial DEA model with a cross-section of N farms, t outputs, and z inputs. The technical efficiency for farm

i can be measured with θ_t.

$$
\begin{gathered}
\min \theta_T \\
\text{s. t. } \sum_{i=1}^{n} \lambda_i Y_{it} \geq Y_{it} \\
\sum_{i=1}^{n} \lambda_i X_{iz} \leq \theta_T X_{iz} \\
\sum_{i=1}^{N} \lambda_i = 1 \\
\lambda_i \geq 0 \\
0 \leq \theta_T \leq 1
\end{gathered}
$$

Now we have the extended input-oriented DEA model with fixed input constraints. In this case, we consider input O to be the farmers' freely chosen input variable. Input F is fixed input that cannot be easily adjusted within the short-run time frame.

$$
\begin{gathered}
\min \theta_a \\
\text{s. t. } \sum_{i=1}^{n} \lambda_i Y_{it} \geq Y_{it} \\
\sum_{i=1}^{n} \lambda_i X_{iO} \leq \theta_a X_{iO} \\
\sum_{i=1}^{n} \lambda_i X_{iF} \leq X_{iF} \\
\sum_{i=1}^{N} \lambda_i = 1 \\
\lambda_i \geq 0 \\
0 \leq \theta_a \leq 1
\end{gathered}
$$

The idea of this model can be easily interpreted through Figure 1 and 2. As demonstrated by Figure 1 where point A represents a farm that is not operating efficiently, the input-oriented radial projection of point A onto the isoquant would be point B. Thus, the radial technical efficiency measure would be $\theta_t = OB/OA$. This implies the farm operator can reduce both inputs and still produce the output level $y = y_0$ using the input bundle B.

Following the extension fixed-input model, Point A's fixed input radial projection onto the isoquant would be point C. In this case, input 2 is held constant while input 1 is our target input. Therefore, θ_a would be CD/AD and input 1 can be reduced by $1 - \theta_a$ without decreasing output.

Figure 2 mirrors Figure 1 by representing the linear programming model in a 3D plot with origin O. In this diagram, the production technology set (production possibility curve) is represented by plane $ABCD$. Point F represents the inefficient farm with output level measured by the length of segment $\overline{\mathrm{IF}}$. The quantity for input 1 can be measured by the length of $\overline{\mathrm{OH}}$ and the the quantity for input 2 can be measured by the length of $\overline{\mathrm{OF}}$. Point E is the reference point on the production frontier for when we hold input 2 constant and only reduce input 1. Point G is the reference point for the simultaneous input reduction. In both cases, the output level is held constant.

V. Dataset

Given that this paper aims to address agricultural nonpoint source pollution from a point source perspective, micro-level farm production information is essential for our analysis. The USDA National Agricultural Statistics Service (NASS) provides two valuable micro-level survey datasets that can be used for this purpose. The first dataset is the Census of Agriculture, a nationwide survey conducted every five years that collects information on farmland use and ownership, production practices, and financial information. The second dataset is the Agricultural Resource Management Survey (ARMS), which is the primary and only source of information available for objectively evaluating many critical issues related to production practices in the U.S. agricultural system.

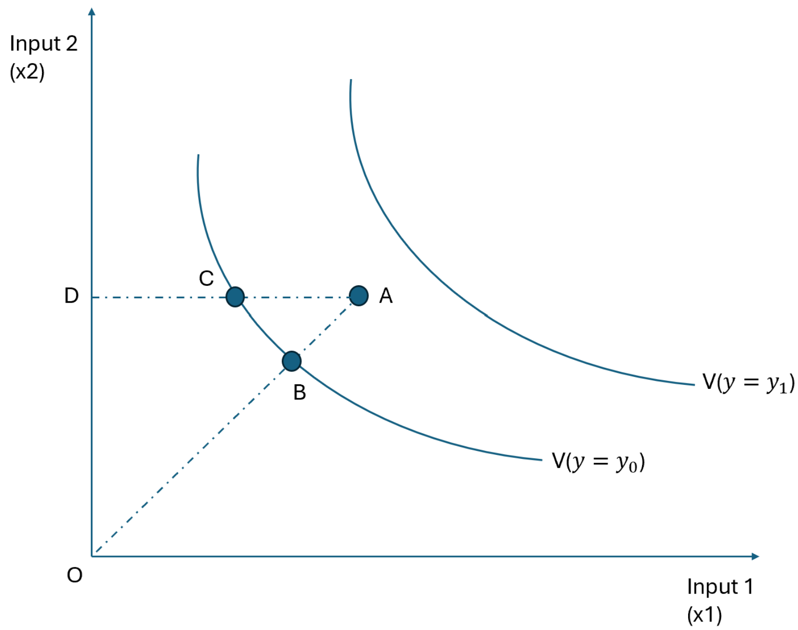

Figure 1. Projection Diagram with Two Inputs and Isoquant

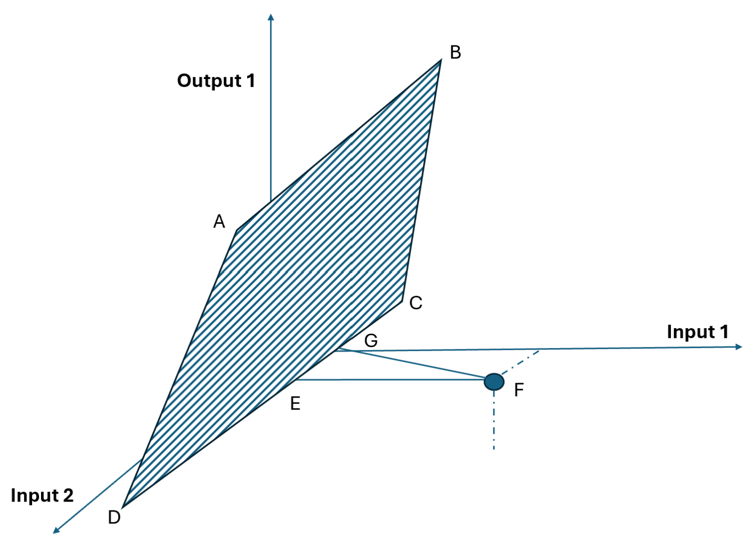

Figure 2. Projection Diagram with Two Inputs and One Output

VI. Estimation Example

As a demonstration of the estimation model proposed in this project, I randomly generated some fake observations based on the information available from the requested variable list of the Ag Census. The purpose of the self-generated pseudo-dataset is to demonstrate the mathematical model/algorithm that can be applied directly to the actual dataset to answer the proposed research problem. Using 35 hypothetical data observations representing 2017 Ag Census Connecticut berry farms, the list of requested variables is summarized in Table 1. [1]

Table 2 provides the unweighted summary statistics for the variables based on 35 self-generated observations. We utilized our background knowledge of Connecticut's small and medium-sized berry farms to ensure the numbers accurately reflect reality. Note that we used the cost of commercial fertilizer, agricultural chemicals, seeds, and fuel instead of their actual quantities, as the survey questionnaire did not explicitly ask for this type of information in quantity volume. It is reasonable to assume that the prices of these inputs do not vary significantly within a particular state in a given year. Therefore, in a cross-sectional analysis, the cost of each input serves as a good proxy for this quantity to do a production efficiency analysis.

In addition, the biggest advantage of constructing the technology frontier using cross-sectional data is that it eliminates the effects of changes in input quality over time. As detailed by Wang et al. (2024), fertilizers used in American agricultural production include more than 50 different combinations of major elements, such as nitrogen (N), phosphorus (P), and potassium (K), and have experienced significant quality changes over time. Similarly, pesticides have altered in terms of potency, persistence, toxicity, absorption rate, and application rate.

Table 3 presents unweighted summary statistics from the radial input-oriented

[1] We opted to use labor quantity rather than labor cost as an input variable to ensure the inclusion of unpaid farm workers in our model. Given that New England farms are often small to medium-sized family businesses, typically operated by a husband and wife, it is crucial to account for family workers when defining labor input.

DEA and the fixed-inputs models. Column 1 indicates that, on average, CT berry farms need only 86.6% of their inputs to achieve the same output. Column 2 shows that a typical CT berry farm can maintain crop yields by reducing commercial fertilizer use by 4% without changing other inputs. Column 3 reveals that these farms can use 74.5% of their current agricultural chemicals while keeping other inputs constant, without reducing output. Lastly, column 4 suggests that CT berry farms, on average, can apply 83.5% of their current chemical levels, maintaining the same output while holding other inputs constant.

To accurately reflect the broader population of CT berry farms, such as compensating for sampling and non-response bias of the survey, the results of the first stage DEA model should be weighted. As demonstrated by Table 4, the second stage summary statistics table of technical efficiency, Column 1 suggests that on average, CT berry farms only need to use 85.4% of all its input to achieve the same output level. Column 2 shows that a typical CT berry farm can maintain the same amount of output by reducing 3.4% of its commercial fertilizer without any change of its other inputs. Similarly, as shown by column 3, a typical CT berry farm can apply 72.8% of its current level of agricultural chemicals and hold other input levels constant without decreasing its output. Lastly, column 4 indicates that CT berry farm, on average, can apply 82% of its current level of all chemicals given the same amount of input.

Table 1—Requested Ag Census Variable List

Variable Name	**Variable Meaning**	**Master_varname_2017**
POID	Farm ID	ID for Farm
K60	State	State of Farm
K1330	Berries Sales Value	Berries Sales Value
K1501	Commercial Fertilizer Cost	Operator (+LL) Expenditure for Commercial Fertilizer
K1502	Ag Chemical Cost	Operator (+LL) Expenditure for Agricultural Chemicals
K1503	Seed Cost	Operator (+LL) Expenditure for Seeds, Bulbs, Etc
K3401	Unpaid Labor Quantity	Unpaid farm workers, number
K941+k942	Paid Labor Quantity	Hired Workers less than 150 Days + Hired Workers 150 Days or More
K1510	Labor Cost (hired farm and ranch labor)	Operator (+LL) Expenditure hired labor
K1511	Labor Cost (contract labor)	Operator (+LL) Expenditure for contract labor
K1507	Fuels Cost	Operator (+LL) Expenditure Dollars for Fuels and Oils
K46	Operational Acres	Total Acres of Land in This Place, Acres
Survey Weight	Ag Census Weight	Ag Census Weight

Table 2—Unweighted Summary Statistics of Variables

Unweighted Summary Stat	**Weight**	**Berry Sales Value**	**Total Labor**	**Commercial Fertilizer Cost**	**Ag Chemical Cost**	**Seed Cost**	**Fuel Cost**	**Operation Acres**
Mean	3.51	39728.23	10.83	11879.74	27.40	24.54	476.11	116.51
Standard Error	0.19	13329.33	1.18	2544.14	2.40	2.58	32.72	24.06
Median	4	7000.00	8	6300	32	25	492	70
Mode	4	1000	5	10000	43	5	736	76
Standard Deviation	1.15	78857.38	6.99	15051.32	14.22	15.28	193.56	142.35
Kurtosis	-0.91	9.53	-0.71	2.02	-1.41	-1.04	-1.12	2.20
Skewness	-0.29	3.08	0.76	1.72	-0.40	0.09	-0.10	1.79
Range	4	349960	24	54996	43	50	688	490
Minimum	1	40	2	4	3	0	106	1
Maximum	5	350000	26	55000	46	50	794	491
Sum	123	1390488	379	415791	959	859	16664	4078
Count	35	35	35	35	35	35	35	35

Unweighted Summary Stat	(1) **InputOrientedTE**	(2) **CFOrientedTE**	(3) **CHEOrientedTE**	(4) **FECHEOrientedTE**
Symbol	θ_t	θ_{CF}	θ_{CHE}	θ_{FECHE}
Mean	0.87	0.96	0.75	0.84
Standard Error	0.03	0.02	0.06	0.05
Median	1.00	1.00	1.00	1.00
Mode	1.00	1.00	1.00	1.00
Standard Deviation	0.19	0.11	0.35	0.27
Sample Variance	0.04	0.01	0.12	0.07
Kurtosis	-0.21	5.90	-0.95	0.64
Skewness	-1.08	-2.64	-0.88	-1.43
Minimum	0.40	0.58	0.10	0.17
Maximum	1.00	1.00	1.00	1.00
Sum	30.31	33.57	26.08	29.24
Count	35	35	35	35

Table 3—Unweighted Summary Statistics of Technical Efficiency

Weighted Summary Stat	(1) **InputOrientedTE**	(2) **CFOrientedTE**	(3) **CHEOrientedTE**	(4) **FECHEOrientedTE**
Symbol	θ_t	θ_{CF}	θ_{CHE}	θ_{FECHE}
Mean	0.854	0.966	0.728	0.82
Count	123	123	123	123

Table 4—Weighted Summary Statistics of Technical Efficiency

VII. Policy Implication

This study aligns well with the USDA Agriculture Innovation Agenda (AIA), which aims to increase U.S. agricultural production by 40% while reducing the environmental footprint by 50% by 2050. This study also echoes the Next Generation Fertilizer Challenges, a joint EPA-USDA initiative that encourages researchers to develop advanced fertilizer formulations to enhance crop yields and environmental outcomes. The empirical model presented in this study serves as a valuable tool for determining optimal fertilizer application dosage for each farm, thereby promoting sustainable agricultural practices. Unlike the Next Generation Fertilizer Challenge, which focuses on fertilizer quality, the model proposed in this study emphasizes the application quality at individual farms. By determining the extent to which agrochemical use can be reduced without impacting output, we can enhance environmental benefits while sustaining agricultural productivity. In addition, this study also helps to sustain the economic viability of American farm operations. Many farmers apply more agrochemicals than necessary, leading to waste and economic inefficiency, which significantly undermines the competitiveness of U.S. agricultural producers.

Additionally, the two-stage estimation model of this project can be used to estimate the theoretical chemical input reduction for other crop type, not just for berry production demonstrated in the example. Corn, the largest consumer of fertilizer in the United States and globally, is a primary crop of interest in the Next Gen Fertilizers Challenge. When applying the empirical model to corn farms, the input choices will differ from those for berries; for instance, corn tractors may be included in the technology set construction. Ultimately, this input-based, data-driven approach to addressing agricultural nonpoint source pollution provides a new solution that can enhance environmental sustainability and support the economic viability of U.S. agriculture.

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