Eco-performance of Crop Producers in Ukraine: A Parametric Approach

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Kommentiert [HO1]: Dear conference organizers,
Obtained results are preliminary, should be revised and checked for robustness. Thus, I would like to ask you to **not** archive the discussion paper on the AgEcon Search repository
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Abstract

Existing empirical literature on crop production in Ukraine mainly focuses on productivity, economic and technical efficiency measures. However, there has been limited evidence on how crop producers perform from an environmental perspective. This study provides the first attempt to empirically estimate the level of eco-efficiency in crop production using farm-level panel data from Ukraine. To address the research question, the hyperbolic environmental technology distance function methodology is employed. Our preliminary results suggest that the average environmental technical efficiency for crop producers in Ukraine is 0.72 over the period 2017-2019. This provides a piece of evidence that a reasonable percentage of crop producers have wide room for improving their environmental performance. Assessing the eco-performance of Ukrainian crop farmers can be relevant for the policy-makers given the growing interest towards a sustainable Ukrainian agricultural sector in view of increasing environmental pressures.

Keywords Eco-efficiency, distance function, stochastic frontier model, crop production

JEL code Q15

1 Introduction

The agricultural sector in Ukraine contributes noticeably to the country's economy by being the third most important sector, after industry and trade, by the share of gross value added in GDP. It also accounts for almost two-fifth of Ukrainian exports (SSSU[1], 2020). At the same time, agriculture is among the top five sectors of the Ukrainian economy adding to the N2O emissions of the country (SSSU, 2018). The agricultural sector, in general, produces along with desirable outputs (crop output in this study) also undesirable ones (such as GHG emissions, pollution from applied chemical fertilizers and pesticides etc.), and they should be both considered in the assessment of the sector's performance. Our focus is on crop production since it accounts for more than three-quarters of Ukrainian agricultural output value (SSSU, 2020).

[1] SSSU – State statistics service of Ukraine, agricultural products accounted for 38% of total export value in 2020

Among the main sources of pollution that come as the environmentally undesirable output of crop production is the extensive application of inorganic fertilizers, especially the uncontrolled use of low-quality fertilizers, that results in N2O emissions and contamination of soil and groundwater (in the case of positive nitrogen and phosphorus balances). The compound annual growth rate of inorganic fertilizers use per hectare in Ukraine was 12% in the last 20 years (Figure 1).

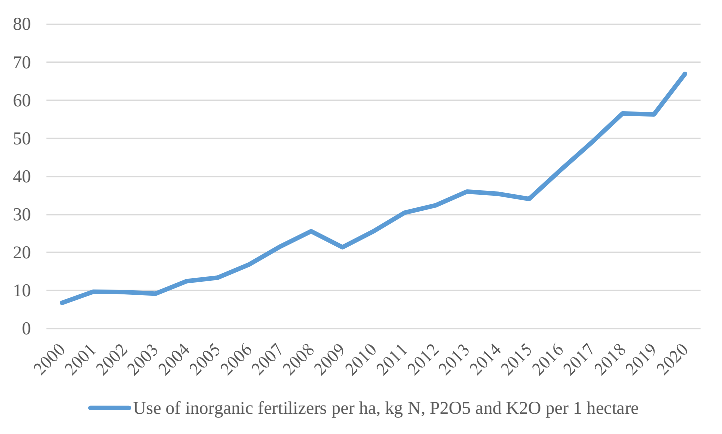

Figure 1. Application of inorganic fertilizers in Ukraine in the last 20 years
Source: Author's presentation based on SSSU data

In the light of the growing level of pollution and environmental pressures in Ukraine amplified by changing climate conditions, Ukraine adopted Environmental Security and Climate Adaptation Strategy until 2030[2]. One of the expected results of its implementation is increasing the efficiency of the state system of environmental impact assessment. Ukraine is also committed to achieving SDG goals that include, among others, promoting sustainable agriculture (Goal 2).

The abovementioned recent developments have heightened the need for empirical research aimed to measure negative agricultural externalities and incorporate them in the evaluation of production performance. Results of such research can inform policy-making in the field of proper management of environmentally undesirable outputs (Mamardashvili et al., 2016). A specific challenging feature of bad outputs is that, unlike desirable ones, their economic values are unknown and are farmers often do not consider them when making their production decisions (Adenuga et al., 2019).

Given the currently available empirical literature, there are virtually no empirical studies that aim to measure the eco-performance of agricultural production in Ukraine. So far, the literature

[2] https://www.kmu.gov.ua/en/news/uhvaleno-strategiyu-ekologichnoyi-bezpeki-ta-adaptaciyi-do-zmini-klimatu-do-2030-roku

has placed focus upon the economic and social aspects of the agricultural sector performance in Ukraine (Lissitsa and Odening, 2005; Balmann et al., 2013; Graubner and Ostapchuk, 2018).

In this paper, our objective is to estimate the level of environmental efficiency of crop producers in Ukraine. Among environmentally undesirable outputs, we consider greenhouse emissions which accompany the application of mineral fertilizers and fuels usage. We employ the parametric hyperbolic environmental technology distance function approach in a stochastic frontier framework with farm-level panel data to analyze the environmental performance of crop producers in Ukraine.

Since up to now, far too little attention has been paid to environmental aspects of agricultural production in Ukraine, this research can contribute to the existing literature by providing the first attempt to shed light on whether and how eco-efficient crop farms in Ukraine might be. The remaining part of the paper is organized as follows: in section 2, we review relevant empirical literature. We provide a detailed description of the data and empirical specification of the model in section 3, while in section 4, the preliminary estimation results are outlined. Finally, we conclude in section 5 by providing an overview of the study findings alongside relevant policy recommendations.

2 Literature review

The generation of undesirable by-products is embedded in many production processes. Agricultural production is not an exception. In case proper inclusion of bad outputs in the analysis is disregarded, this not only precludes from crediting farms' productivity and efficiency for a ceteris paribus reduction in undesirable outputs but also questions the reliability of the estimates of a desirable production (Kumbhakar and Malikov, 2018).

Among approaches to modelling bad outputs, a few categories can be distinguished. They include are a multi-equation representation of polluting technology and an alternative single-equation specification of the production process in the presence of bad outputs (Kumbhakar and Malikov, 2018). Formalization of the pollution-generating technology under the single-equation approach is usually in the form of distance functions. The existing empirical literature suggests various types of them. They include the radial input or output distance functions, the directional output distance function and the hyperbolic distance function. The main features of these distance functions are outlined in Table 1.

Table 1. Most widely used distance functions

<table>
<tr><th>Distance function</th><th colspan="2">Description</th></tr>
<tr><td>Radial output/input</td><td colspan="2">treats desirable and undesirable outputs symmetrically</td></tr>
<tr><td>Directional</td><td rowspan="2">enable the expansion of desirable output and contraction of undesirable output simultaneously</td><td>makes use of the translation homogeneity property</td></tr>
<tr><td>Hyperbolic</td><td>is based on the multiplicative homogeneity property</td></tr>
</table>

Source: Based on Adenuga et al. (2020)

There are two ways of estimating distance functions: non-parametric and parametric. Both techniques have their advantages and limitations (Appendix 1). In particular, the non-parametric approach (Data Envelopment Analysis) does not require the specification of a functional form that allows avoiding confounding the effects of misspecification of the functional form with those of inefficiency. However, this technique is sensitive to extreme values and inference is not possible without bootstrapping (Adenuga et al., 2018). At the same time parametric approach, namely stochastic frontier analysis (SFA) attempts to distinguish the effects of noise from those of inefficiency, thereby providing the basis for statistical inference (Bravo-Ureta et al., 2015). However, since SFA requires the specification of a functional form for the production technology, its results might be affected by possible misspecification of the functional form. Thus, basically, the limitations of the parametric approach are the advantages of non-parametric and vice versa.

Selected parametric approaches used in the empirical literature to account for undesirable outputs are presented in Appendix 2. Among them, the application of the hyperbolic distance function approach has been popular in recent years, including in the field of agricultural economics (Table 2). In our study, we also adopted the parametric hyperbolic distance function with a flexible translog functional form.

Table 2. Studies that employed the hyperbolic distance function in agricultural economics

Study	**Application**
Suta, Bailey, and Davidova (2010)	used the hyperbolic distance function approach to estimate the environmental technical efficiency scores of selected EU farms
Mamardashvili, Emvalomatis, and Jan (2016)	applied the hyperbolic distance function to assess the environmental performance of conventional and organic Swiss dairy farms using cross-sectional data; estimated the shadow price of nitrogen surplus
Rosano-Peña et al. (2018)	showed the possibility of producing more with less environmental impact and less use of resources in the agriculture of the municipalities comprising the Brazilian Amazon biome employing the parametric hyperbolic distance function approach
Skevas et al. (2018)	used the hyperbolic distance function approach to analyze and evaluate the impact of policies and intensification on the environmental performance of Dutch dairy farms in the period 2001–2010
Adenuga et al. (2019)	Applied a parametric hyperbolic technology distance function approach to estimate environmental efficiency in dairy farms, calculated pollution costs of nitrogen surplus
Adenuga et al. (2020)	analyzed the environmental technical efficiency and shadow price of phosphorus surplus in dairy farms employing the hyperbolic environmental technology distance function in a stochastic frontier analysis framework.

Source: Based on Adenuga et al. (2020)

3 Data and empirical specification of the model

To address the research question, we use recent farm-level accounting and crop production data collected by the State Statistics Service of Ukraine (SSSU). These are panel data covering crop production of agricultural producers in the period of 2017-2019. We create a balanced panel with a focus on the production of cereals (including wheat, barley, maize and others) and sunflower, which are major crops in terms of sowing land and output shares (Figure 1).

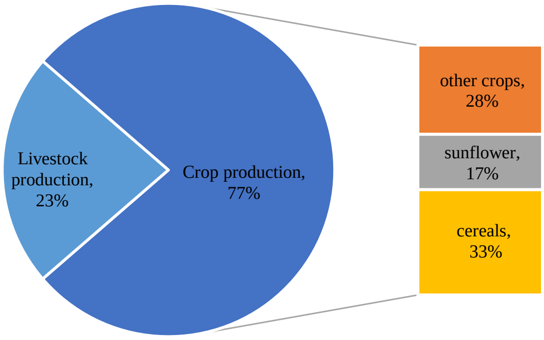

Figure 1. Structure of agricultural output in Ukraine in 2020
Source: Author's presentation based on SSSU data

Production of selected crops is concentrated mainly in the south-eastern part of Ukraine, which lies in the steppe agro-climatic zone (Figure 2). This climatic zone is characterized by dry and very warm conditions (Graubner and Ostapchuk, 2018).

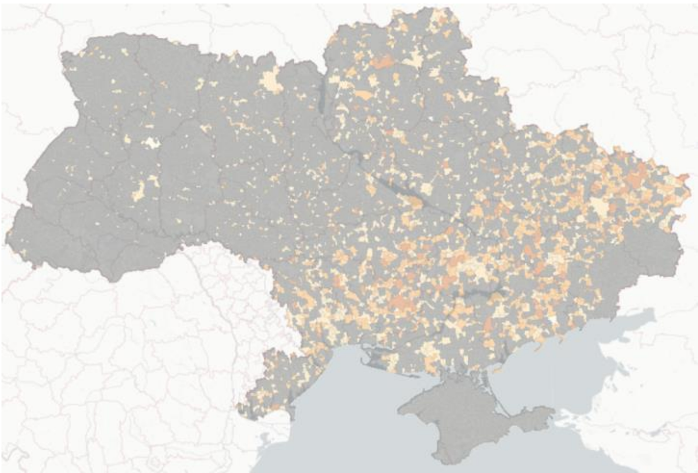

Figure 2. Location of cereals and sunflower production in Ukraine
Source: Author's presentation

We estimate crop farms' environmental efficiency by applying an econometric model based on a parametric hyperbolic technology distance function approach, which allows including both desirable and undesirable outputs (Mamardashvili et al., 2016, Adenuga et al., 2019). Yields of cereals and sunflower enter our analysis as desirable outputs, while greenhouse emissions (N2O and CO2 emissions) originating from the application of mineral fertilizers and fuels' usage are considered undesirable outputs. Selected in our analysis crops, cereals and sunflower, account for a noticeable share of total chemical fertilizers application (63% and 21% respectively in 2020).

Following Adenuga et al. (2019) the empirical specification of the stochastic hyperbolic environmental technology distance function is presented in equation 1.

$$-\ln y_{1,it} = \beta_0 + \sum_{j=1}^{4} \beta_j \ln x_{j,it} + \frac{1}{2} \sum_{j=1}^{4} \sum_{j'=1}^{4} \beta_{jj'} \ln x_{j,it} \ln x_{j',it} + \varphi_2 \ln \frac{y_{2,it}}{y_{1,it}} + \frac{1}{2} \varphi_{22} \left(\ln \frac{y_{2,it}}{y_{1,it}} \right)^2 +$$

$$+ \sum_{k=1}^{2} \gamma_k \ln\left(b_{k,it} \cdot y_{1,it}\right) + \frac{1}{2} \sum_{k=1}^{2} \sum_{k'=1}^{2} \gamma_{kk'} \ln\left(b_{k,it} \cdot y_{1,it}\right) \ln\left(b_{k',it} \cdot y_{1,it}\right) + \sum_{j=1}^{4} \omega_{j2} \ln x_{j,it} \ln \frac{y_{2,it}}{y_{1,it}} +$$

$$+ \sum_{j=1}^{4} \sum_{k=1}^{2} \delta_{jk} \ln x_{j,it} \cdot \ln\left(b_{k,it} \cdot y_{1,it}\right) + \sum_{k=1}^{2} \mu_{2k} \ln \frac{y_{2,it}}{y_{1,it}} \cdot \ln\left(b_{k,it} \cdot y_{1,it}\right) + \sum_{l=1}^{6} \rho_l z_{l,nt} + (v_{it} - u_{it}) \tag{1}$$

where x_j – inputs
$y_{1,2}$ - desirable outputs
b_k – undesirable outputs
z_l - additional factors that influence the production process
i=1,2,..,N represents the observed crop farms in time t=1,2,..,T.

For variables that contain zero values, inverse hyperbolic sine transformation was used instead of logarithmic transformation.

Coefficients of the hyperbolic output distance function are estimated based on the error components frontier model with a Translog specification for the underlying production function (Battese & Coelli 1992). We control for additional explanatory variables that influence the production frontier, such as climatic variables, irrigation and pesticide practices. The conditional distribution of the inefficiency components was obtained following a half-normal distribution. In addition, as a robustness check, the model with a Cobb-Douglas specification of production function is estimated. The results are presented in Appendix 4. There is a considerable difference in the results of the two specifications concerning labour input, estimated elasticity doesn't follow monotonicity condition in a Cobb-Douglas specification. Results of the likelihood ratio test (χ^2=225.37) clearly reject the Cobb-Douglas output distance function in favour of the Translog output distance function.

All output and input variables were scaled by their geometric mean, consequently, the estimated first-order parameters can be interpreted as elasticities at the sample mean of the data (Färe et al., 2005; Cuesta, et al., 2009). All the variables measured in monetary units are in constant prices of 2019. They were corrected for inflation using the appropriate annual producer price indices published by the State Statistics Service of Ukraine (SSSU, 2020). The time-variant environmental technical efficiency estimates were calculated for each farm by using the point estimator proposed by Battese and Coelli (1988) given in equation (2):

$$ETE = E(e^{-u_{it}}|\varepsilon_{it}) \quad (2)$$

The variables included in the analysis are selected based on the underlying production process of specialized crop farms. The following inputs (x_j) are included in the specification of hyperbolic environmental technology distance function:

1. sowing land area under cereals and sunflower,
2. capital measured in terms of depreciation values,
3. labour measured in the cost of labour services,
4. variable inputs, which consist of costs of seed, fertilizers, energy and other materials

Regarding outputs, the desirable ones include:
1. cereals output ($y_{1,}$ to impose the almost homogeneity condition, it was chosen for normalizing),
2. sunflower output (y_2)

While considered undesirable outputs (b_k) are
1. N2O emissions originating from the application of mineral fertilizers
2. CO2 emissions from fuels' usage

We made use of emission coefficients to get values for both undesirable outputs. In particular, N2O emissions were calculated using equation (3)[3]:

$$N2O = \sum_{j=0}^{n}(q_j \cdot c_j) \cdot e \cdot \frac{44}{28}$$

q_j - quantity of purchased chemical fertilizer of each type
c_j - percent of nitrogen each type of fertilizer contains
e - emission coefficient, which equals 0.0117 tons N2O-N/ton N applied
44/28 - The molecular weight ratio of N2O to N2O as N (N2O/N2O-N)

For chemical fertilizers, the quantity of nitrogen was found in the commercial product label (Appendix 3). When it comes to CO2 emissions, their level was calculated as a product of the amount of purchased fuel by type and corresponding emission factor (Appendix 4).

Given that crop production is sensitive to climatic conditions, we control for the mean and standard deviation of daily temperature in the district where the farm is located as well as for sum and standard deviation of daily precipitation level. Also, our model includes dummies

[3] Based on AP 42, Fifth Edition, Volume I Chapter 14: Greenhouse Gas; United States Environmental Protection agency: https://www.epa.gov/air-emissions-factors-and-quantification/ap-42-fifth-edition-volume-i-chapter-14-greenhouse-gas-1

outlining whether crops are irrigated and whether any type of pesticide, herbicide or insecticide (PHI) is used.

Our balanced panel data set consists of 1722 observations for 574 crop producers specializing in cereals and sunflower. A summary statistic of the variables included in the model is given in Table 3.

Table 3. Descriptive statistics of the variables included in the model (averages across three years period)

Variables	Mean	Std. Dev.	Min	Max
Desirable outputs				
Cereals output, tonne	2,497.8	4,570.4	15.3	114,079.8
Sunflower output, tonne	974.8	1,735.2	0.0	25,766.9
Inputs				
Sowing land, ha	1,027.4	1,164.4	2.0	16,816.5
Capital, '000 UAH	1,234.4	2,470.7	0.0	29,320.9
Labor, '000 UAH	1,032.7	1,853.3	0.0	34,511.1
Variable input, '000 UAH	9,725.0	14,432.1	0.0	217,308.7
Undesirable outputs				
N2O emissions, tonne	1.6	3.0	0.0	47.0
CO2 emissions, tonne	54.1	333.7	0.0	12,900.0
Additional explanatory variables				
Annual mean temperature, °C	8.9	1.8	5.0	13.2
Annual sd temperature, °C	9.9	1.4	6.8	12.5
Sum of precipitation, mm	3,847.2	1,591.7	626.9	12,002.8
Sd of precipitation, mm	4.5	0.9	2.8	7.0
Irrigation dummy	0.0	0.1	0.0	1.0
PHI dummy	0.8	0.4	0.0	1.0

4 Empirical Results and Discussion

Selected parameter estimates and the associated standard errors of the parametric hyperbolic distance function model are presented in Table 4 (see Appendix 5 for full results).

Since the left-side variable in equation (1) has a negative sign, distance elasticities of inputs, other output, and undesirable outputs variables in the model possess the expected sign at the mean of the data. Negative signs of inputs and the undesirable outputs parameters imply that an increase in them makes the farm further away from the production frontier, while a positive sign of desirable output parameter means that increase in it, for a given input and undesirable output vectors, brings the farm closer to the production frontier (Adenuga et al., 2019). Thus, the parameter estimates of the hyperbolic distance function satisfy the monotonicity conditions at the sample mean: non-decreasing in desirable outputs and non-increasing in undesirable outputs and inputs (Skevas et al., 2018; Cuesta and Zofío, 2005).

Table 4. Selected parameter estimates of the hyperbolic environmental technology distance function

Parameter		Estimate (Standard error)
β_1 (land)		-0.872*** (0.054)
β_2 (labor)		-0.004 (0.064)
β_3(capital)		-0.081 (0.059)
β_4(variable inputs)		-0.299* (0.123)
γ_{b1} (N2O emissions)		-0.166*** (0.052)
γ_{b2} (CO2 emissions)		-0.287*** (0.057)
φ_2 (sunflower output)		0.393*** (0.044)
z_1 $(sum\ precipitation)$		0.000*** (0.000)
z_2 $(sd\ precipitation)$		0.005 (0.012)
$z_3(mean\ temperature)$		0.094*** (0.012)
$z_4(sd\ temperature)$		0.092*** (0.016)
$z_5(irrigation\ dummy)$		-0.114 (0.088)
$z_6(pesticides\ dummy)$		-0.076*** (0.023)
$sigmaSq$		0.257*** (0.02)
$gamma$		0.783*** (0.02)
$Efficiency$		
Mean	2017	0.730
	2018	0.726
	2019	0.722
Min		0.156
Max		0.969

The preliminary results of the analysis showed that the average eco-efficiency estimate of crop producers in Ukraine is 0.72, with virtually no variation over the considered years. The histogram of the hyperbolic efficiency estimates exhibits a conventional left-skewed pattern (Figure 3). There is a quite low level of heterogeneity in environmental technical efficiency across crop farms. These estimates imply that, on average, producers of cereals and sunflower in Ukraine can improve their production results by increasing crop output by 39%

(1/0.72=1.388) and simultaneously contracting undesirable outputs by 28% (1-0.72=0.28). Additional explanatory factors included in the model, such as mean temperature and total precipitation levels, appeared to have a highly statistically significant effect on crop output, while the effect of the irrigation dummy is not statistically different from zero.

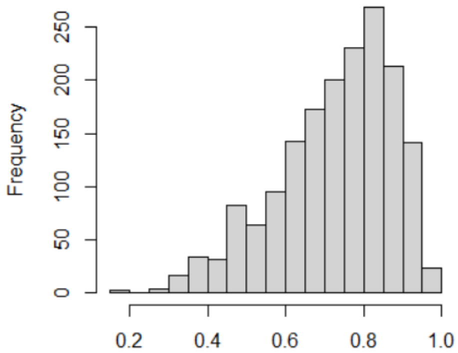

Figure 3. Distribution of environmental technical efficiency of crop producers

5 Summary and Concluding Remarks

Among outputs of crop production, there are not only desirable such as crop yields, but also environmentally undesirable ones such as GHG emissions. Negative agricultural externalities are an important, but understudied, cause for concern in Ukraine. This study emphasizes the necessity of accounting for both types of outputs when assessing the performance of agricultural producers. Thus it aimed to evaluate the environmental performance of crop producers in Ukraine. In this study, we used balanced panel data covering the production of two major crops (cereals and sunflower) in the period of 2017-2019. This paper contributes to the existing literature by providing the first estimates of the eco-efficiency of crop producers in Ukraine. The results indicate how (in)efficiently farms are performing, which reflect the maximum possible level of desirable outputs and minimum level of bad outputs given the quantities of inputs used. Estimated efficiency levels imply that a reasonable percentage of crop producers have a wide room for improving their environmental performance.

The main limitations of this study are, to a great extent, driven by data availability. Firstly, we do not account for an important undesirable outputs of crop production, such as nitrogen and PHI pollution. This is due to the unavailability of data on the application of organic fertilizers that are required for the calculation of nitrogen balance. When it comes to PHI application, data contain only aggregated quantities without details on the particular type of pesticide, herbicide or insecticide used. Secondly, our panel data is quite short that leads to a lack of dynamic perspective and prevents capturing of technical change. Lastly, there are virtually no data on potential conventional determinants of inefficiency (such as farm economic size, land type, environmental subsidies etc).

In this context our recommendations are mainly in the field of data collection and addressed to the State Statistics Service of Ukraine. To enable robust and comprehensive estimation of the environmental performance of agricultural producers, an annual statistical form filled by agricultural producers should contain more detailed information on all types of fertilizers and pesticides used along with farm characteristics.

Regarding policy recommendations, to enhance the eco-efficiency of crop producers, it is important to restrict amounts of inorganic fertilizers that can be used, establish clear standards on the quality of fertilizers that can be applied, and promote the application of organic fertilizers. Also, government support of programs for farmers related to improving energy savings (for instance, installing new high-efficiency motors) will help to reduce the amount of farm CO2 emissions.

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Appendices

A.1 Advantages and limitations of parametric and non-parametric techniques

<table>
<tr><th colspan="2">Method</th><th colspan="2">Main feature</th><th>Advantage</th><th>Limitation</th></tr>
<tr><td rowspan="2">Parametric</td><td>Deterministic frontier analysis</td><td rowspan="2">Require the specification of a functional form for the production technology</td><td>Assumes that any deviations from the frontier stem from inefficiency</td><td></td><td>Measurement errors, as well as other sources of random variation are captured as inefficiency</td></tr>
<tr><td>Stochastic frontier analysis (SFA)</td><td>incorporates statistical noise</td><td>Attempts to distinguish the effects of noise from those of inefficiency, thereby providing the basis for statistical inference;

Estimation of multi-input multi-output models employing input and output distance functions</td><td>Effects of a possible misspecification of functional form</td></tr>
<tr><td>Non-parametric</td><td>Data Envelopment Analysis (DEA)</td><td colspan="2">Does not require the specification of a functional form</td><td>Avoids confounding the effects of misspecification of the functional form with those of inefficiency;

Ability to easily accommodate multi-input multi-output technologies within a primal specification</td><td>Is deterministic and thus sensitive to extreme observations; can be sensitive to the number of observations in the data and to the dimensionality of the frontier</td></tr>
</table>

Source: Based on Bravo-Ureta et al. (2015)

A.2 Selected parametric approaches used in the empirical literature to account for undesirable outputs

Method	Description	Reference(s)
A Parametric Hyperbolic Technology Distance Function Approach	The hyperbolic distance function can treat desirable and undesirable outputs asymmetrically by seeking to simultaneously expand desirable outputs and contract undesirable outputs	Adenuga, Davis, Hutchinson, Donnellan, Patton (2019) Mamardashvili, Emvalomatis, and Jan (2016)
A panel frontier system model with good and bad outputs and endogenous treatment decision	▪ A simultaneous panel stochastic frontier system for the production of good and bad outputs when inefficiency is present in both; ▪ Treatment of bad output is considered when the treatment decision is endogenous; ▪ Because of simultaneity, inefficiency from the production of good (bad) output is transmitted to the production of bad (good) output.	Lai and Kumbhakar (2021)
A Hedonic Output Index based Approach to Modeling Polluting Technologies	Technology is modelled by using two functions: ▪ an input distance function describing technically feasible input-output combinations, ▪ and a hedonic output function capturing relationships among good and bad outputs.	Malikov, Bokusheva and Kumbhakar (2018)

A.3 Nitrogen content by mineral fertilizers type

Type of fertilizer	**% nitrogen**
Nitrogen mineral fertilizers	
ammonium sulfate	21
ammonium nitrate	35
urea	46
ammonium saltpeter	34.4
liquid ammonium fertilizers	82.3
ammonia water	20.5
urea-ammonia mixture	32
Phosphate mineral fertilizers	
superphosphate granulated with boron	10
superphosphate simple powder	10
double granular superphosphate	10
Complex mineral fertilizers	
amophos	11
nitroammophoska	16
nitrophos	9
fertilizer mixture	13
ammophosphate	10
azophos	21

A.4 Emission coefficients by fuel type

Fuel type	**Initial units**	**Units conversion**	**kgCO2**
Motor gaseline	tonne	1 ton= 31.755 gallon 1 tonne=35.004 gallon	8.78 per gallon
Diesel fuel	tonne		10.21 per gallon
Heavy gas oil	tonne		11.09 per gallon
Petroleum oil	hundredweight	1 hundredweight=0.056 ton 1 hundredweight=1.778 gallon	5.68 per gallon
Coal	tonne	1 tonne (metric)=1.10231 short ton	2.819 per short ton
Natural gas	thousand m3	1 m3=35.311 standard cubic foot	0.05444 per scf

Source: Report of U.S. Environmental Protection Agency

A.5 Parameter estimates of the hyperbolic environmental technology distance function for different production technologies

Parameter	Estimate (Standard error)	
	Cobb-Douglas	Translog
β_1 (land)	-0.811*** (0.02)	-0.872*** (0.054)
β_2 (capital)	-0.009* (0.005)	-0.081 (0.059)
β_3(labor)	0.027*** (0.008)	-0.004 (0.064)
β_4(variable inputs)	-0.129*** (0.016)	-0.299* (0.123)
γ_{b1} (N2O emissions)	-0.039*** (0.004)	-0.166*** (0.052)
γ_{b2} (CO2 emissions)	-0.038*** (0.005)	-0.287*** (0.057)
φ_2 (sunflower output)	0.859*** (0.02)	0.393*** (0.044)
β_{11}		0.041* (0.023)
β_{22}		0.013 (0.046)
β_{33}		0.088** (0.044)
β_{44}		0.118 (0.133)
β_{12}		0.012 (0.032)
β_{13}		0.003 (0.037)
β_{14}		0.126** (0.063)
β_{23}		0.049 (0.031)

β_{24}		0.038 (0.055)
β_{34}		0.030 (0.055)
φ_{22}		0.157*** (0.02)
γ_{b1b1}		-0.068** (0.033)
γ_{b2b2}		0.001 (0.026)
γ_{b1b2}		0.028 (0.019)
δ_{1b1}		0.114*** (0.036)
δ_{2b1}		-0.063** (0.026)
δ_{3b1}		-0.046* (0.024)
δ_{4b1}		0.115** (0.055)
δ_{1b2}		-0.019 (0.038)
δ_{2b2}		-0.002 (0.029)
δ_{3b2}		-0.024 (0.025)
δ_{4b2}		-0.030 (0.049)
ω_{1y2}		0.011 (0.021)
ω_{2y2}		0.009 (0.022)
ω_{3y2}		-0.043 (0.027)
ω_{4y2}		-0.111** (0.047)
μ_{b1y2}		-0.036 (0.029)
μ_{b2y2}		0.057* (0.03)
z_1 $(sum\ precipitation)$	0.000*** (0.000)	0.000*** (0.000)
z_2 $(sd\ precipitation)$	0.010 (0.012)	0.005 (0.012)
$z_3(mean\ temperature)$	0.113*** (0.012)	0.094*** (0.012)
$z_4(sd\ temperature)$	0.116*** (0.016)	0.092*** (0.016)
$z_5(irrigation\ dummy)$	-0.078 (0.098)	-0.114 (0.088)
$z_6(pesticides\ dummy)$	-0.023 (0.025)	-0.076*** (0.023)

sigmaSq		0.326*** (0.025)	0.257*** (0.02)
gamma		0.809*** (0.018)	0.783*** (0.02)
time		-0.054** (0.019)	-0.019 (0.021)
Efficiency			
Mean	2017	0.717	0.730
	2018	0.705	0.726
	2019	0.693	0.722

Notes: Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5% and 1% level