Objections to some conventions in non-parametric analyzes of regional agricultural production.

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Abstract

Nonparametric analyzes of regional agricultural production is frequently motivated by sustainability goals. In theory, an efficient allocation of production inputs and increased production outputs induced by innovations and technical progress could allow to save on scarce natural resources while simultaneously expanding the provision of food and fiber. Policy recommendations derived from two-stage analyzes thus confidently advise policy makers and farmers to modernize, specialize or scale up to counteract technical inefficiency. In this paper two major objections are presented to these conventions within the agricultural economics literature. First, we show that when spatially differing climatic conditions are sufficiently considered in two-stage analyzes, conventional policy recommendations are not valid anymore. Second, we argue that from a production-theoretic point of view, the traditionally employed technical efficiency model fails in providing information on sustainability of agricultural production. We thus suggest to conceptually decompose technical efficiency into an operational and a physical efficiency measure. For the period 2004 to 2018, we find a stagnating trend in physical productivity in the agricultural sectors of 122 European regions. In conjunction with the subordinate role of contextual to environmental determinants of inefficiency we propose to neither motivate studies with sustainability goals by default nor derive policy recommendations whenever the impact of environmental factors is not sufficiently considered.

Keywords: technical efficiency, regional analysis, DEA, Malmquist-productivity index, environmental factors, nonparametric analysis, Tobit regression, panel data, sustainability

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1 Introduction

Just recently, Hansson, Manevska-Tasevka and Asmild (2020) have raised an important question regarding the interpretation of inefficiency obtained in non-parametric analyzes. What if the decision-makers chose to conduct their farming business (at least to some degree) inefficiently? What if they acted rationally and based their decisions on considerations remote to the agricultural economist such as a preference for high animal welfare or other extensive practices? The authors convincingly argue that the contribution of studies that provide policy recommendations in order to nudge inefficient farmers to catch-up with sample peers is limited whenever the rational choice of the decision-maker is not sufficiently considered.

In this paper we would like to build on the authors' rationale by posing a different question. What if the decision-maker is not capable of choosing between conducting his farming business more or less productive? What if the varying degrees of inefficiency found in non-parametric analyzes are determined by spatially differing factors outside of the sphere of influence of both policy and decision-makers? In such cases, policy recommendations would not only miss out on acknowledging rational production decisions but potentially even harm farmers by erroneously urging them to invest in what is referred to in the literature as better allocation of production inputs (Toma et al. 2017) by means of specialization (Galluzzo 2022), technological modernization (Nowak, Kijek and Domańska 2015), or operating on optimal scale (Galluzzo 2013).

One might object that studies have hardly ever discussed factors that are determinate in the sense of being neither controlled by policy- and decision makers as explanatory factors of inefficiency. Indeed, the majority of studies in the literature is dedicated towards examining the effect of regionally differing sectoral characteristics such as size, specialization, or subsidies, which are of course subject to and manipulated by farmers or agricultural policies. Given the growing importance of studies on environmental efficiency or motivating efficiency analyses with sustainability goals, the neglection of determinate i.e., climate related factors, as a potential driver of (in-)efficiency comes as a surprise. Apart from some notable exceptions (, which will be adressed in the upcoming literature review section) few authors acknowledge the role environmental features play in explaining inefficiency variation and the consequences this might bear for studies' policy implications.

Following this line of thought, we'd further like to critically discuss the idea perpetuated in the literature that non-parametric efficiency and productivity analyzes are suitable tools in assessing the sustainability of (regional) agricultural production. A considerable amount of studies motivate conducting technical efficiency analysis with sustainability goals, e.g., pointing at 'the potential for increasing agricultural production in the EU, balancing environmental resource savings with economic return. (Toma et al. 2017: 140)' or the need for 'growth in agricultural productivity and a more efficient way of utilizing limited inputs […] [if] output is to keep up with the increasing demand for food and raw materials (von Hobe, Michels and Musshoff 2021: 2)'. In theory, rising productivity figures should reflect an improved feasibility in expansion of production possibilities, either induced by advanced technology or skills. The latter in turn are supposed to enable producers to increase (or maintain) agricultural produce output, utilizing constant (or less) resource input quantities. Arguably though, findings of most productivity analyses may allow to support this motivation only to a very limited extent, because the technical efficiency model conventionally employed, contains only limited information on actual physical produce and resources. We thus suggest decomposing the latter into an efficiency model based on physical production factors and an efficiency model built on an operational input-output set.

Empirical results for crop and mixed farms of 122 EU regions in the period 2004 to 2018 show that climatic conditions i.e., radiation, temperature and precipitation levels are statistically and economically significant in explaining efficiency variation. Given all other model parameters remain constant, we find that an increase in mean regional temperature of one degree Celsius already accounts for 1.5 % of (input-oriented technical) inefficiency variation. The results for the 'operational' and 'physical' model efficiency affirm the claim that agricultural production efficiency substantially depends on neglected determinate factors. For the former, environmental and usually considered sectorial features e.g., economic size or intensity of practices, are found to determine a decision-makers degree of inefficiency. For the latter in turn, regional sectoral characteristics seem to play a subordinate role and inefficiency variation can mostly be attributed to spatially differing climatic conditions. In case, the latter are not sufficiently accounted for in efficiency analyses, inefficiency might be wrongfully attributed to decision-makers and policy recommendations misleading.

Findings of the productivity analysis reveal that the claim of future increases in (technical) productivity, contributing towards a harmonization of saving on natural resources while expanding provision of food and fiber, is questionable at least. Although our findings do suggest an increase in technical productivity, productivity for our physical efficiency measure is stagnating, suggesting that further expansion of agricultural produce in accordance with environmentally sound production conditions, might be overestimated. As a consequence, motivating technical efficiency and productivity analyses with sustainability goals by default seems inadmissible.

The remainder of the paper is organized as follows. The literature review in section 2 provides proof that the conventions lined out above exist and discusses why they are problematic above all in the context of regional agricultural production. In section 3, the theoretical framework for the empirical application case and the conceptual decomposition of technical efficiency and is introduced. In section 4, results of the efficiency, (Malmquist-) productivity and second stage random effects Tobit panel regression analysis are discussed. The paper closes with concluding remarks in section 5.

2 Literature Review

Of course, not all studies on agricultural production efficiency and productivity employing nonparametric methods are affected by the issue outlined above. Whether or not the neglection of environmental factors leads to deterred policy implications depends on a variety of factors, above all the scope of the analysis and how its results are interpreted.

In the agricultural economics literature, the scope of studies varies significantly. Roughly, they may be divided in analyzes of efficiency (mostly) using cross-sectional data on the one hand and analyzes of productivity based on panel data on the other. Some works focus on specific farm types, e.g., dairy, crop or mixed farms and are conducted either on farm-level, regional, country or even global scale. Clearly, not all frameworks are equally vulnerable to the influence of determinate factors such as climatic conditions. In farm-level analyses of dairy farms for example, ecological features are expected to have a less pronounced effect on inefficiency variation when compared to productivity estimates of arable farms in a global scale setting. The criticism outlined in the introduction thus concerns studies to a different degree and above all applies to analyses conducted at least on a regional level.[1]

And even in studies examining efficiency on regional or even broader scope, the issue does not necessarily have to arise. An example for a concise and sound country-level analysis is provided by Coelli and Rao (2005), in which agricultural total factor productivity of 93 countries is examined by employing the (nonparametric) Malmquist Productivity Index. The authors argue that their findings are mainly of interest because they show a reversal in the productivity trend reported by previous studies. They further argue that future research should consider land quality, irrigation, and rainfall levels to allow for a more meaningful interpretation of the differences that exist between the countries' efficiency numbers. The conclusions drawn by the authors are thus exclusively based on a relative comparison with other studies, make no judgments on why decision-makers might be inefficient and neither provide policy recommendations on how to enhance productivity levels.

The latter is of course legitimate whenever environmental factors are explicitly and sufficiently accounted for within the methodological framework. Chambers, Hailu and Quiggin (2011) proposed a methodology to account for event-specific uncertainty in agricultural production. They showed how Data Envelopment Analysis (DEA) can be adapted to consider stochastic elements in a state-contingent setting. Their findings suggest that different quantities of rainfall influence agricultural efficiency estimates. A similar approach was pursued by Gadanakis and Areal (2020), who derived the efficiency scores based on sub-vector DEA to ensure that only farms with homogenous environmental conditions were compared. In another article, Chambers, Pieralli and Sheng (2020) incorporated climatic variates directly into the productivity accounting framework and decomposed the productivity growth measured (among others) into a technological change and a weather-related change component. Their

[1] One should note though, that an impact of environmental variables on efficiency cannot be ruled out completely in agricultural production contexts. Schmitt et al. (2022) showed that extreme weather events caused significant crop yield losses at farm level, which suggests that environmental factors might even affect inefficiency distributions in farm-level analysis.

results suggest that the observed slowdown in Australian agricultural productivity growth is not attributable to a slowdown in technological change but much rather induced by weather-related events. Chambers and Pieralli (2020) confirm the importance of climatic features by applying the method to the case of US agricultural production.

Given that some studies are not affected due to a specific scope or a careful interpretation of the results and other analyzes explicitly account for the effect of environmental factors, one might question the relevance of the issue outlined in the introduction section. Even though the cases introduced here exist, they are by no means the norm. Let's move from the exception to the rule.

Instead of applying a methodology as described above, the two-stage analysis is the most popular approach to determine efficiency of decision-makers and explanatory factors of inefficiency. The two-stage approach comprises calculating DEA estimates in a first step, before regressing on the yielded efficiency estimates in a censored or truncated regression model in the second stage. In the latter, the effect of contextual variables (within the sphere of influence of the decision-maker) is considered. In context of agricultural production these variables include but are not limited to e.g., size, specialization, and subsidies. A direct incorporation of climatic variates into the efficiency framework (of the first stage) as in the example of Chambers, Pieralli and Sheng (2020) is not intended. Interestingly, the issue equally arises in eco- or environmental efficiency analyses (e.g., Baležentis et al. 2020; Grassauer et al. 2021; Yang, Wang and Bin 2022), which consider not climatic conditions but environmentally undesirable outputs, e.g., nutrient surpluses, within their efficiency model. When efficiency estimates reflect results on the latter, they are presumably even more sensitive to the impact of the climatic conditions with which they interact.

While a few studies employing the two-stage approach consider environmental factors in the second stage of the analysis, there is no discussion of the consequences this might bear for policy implications (e.g., Heidenreich et al. 2022). In fact, in one particular case, soil quality is found to have a significant impact on inefficiency (, whereas the effect of other considered covariates is unclear), yet authors formulate mantra-like calls for investments in modernization to enable technological progress (Nowak, Kijek and Domańska 2015). In addition, there are plenty of examples, where studies ignore potential impact of environmental factors, yet suggest more or less concrete policy measures, such as enhancing farmers' knowledge and managerial skills (Todorović et al. 2020), correction of scale and improvement of technology (Błażejczyk-Majka, Kala and Maciejewski 2012), learning processes and imitation of technologies (Baráth and Fertő 2017), removing misallocation of resources by investing in agricultural extension systems (Bagchi, Rahman and Shunbo 2019), agricultural innovation (He, Li and Cui 2021).

In some of the above cases (e.g., Galluzzo 2013, Galluzzo 2022; Nowak, Kijek and Domańska 2015) these recommendations are not based on statistical and economic significance of sectoral characteristics. Much rather it seems to be an accepted convention to provide some general economic advice on how to enhance productivity. We do not mean to propose that none of the inefficiency found in these analyses cannot reasonably be targeted by such measures. Also, one might be tempted to say that modernizing farm equipment, acquiring new skills or adopting best practices should not be harmful either way. Nonetheless, we would argue that this is not well thought out. The above-mentioned policy recommendations require for substantial investments in either machinery, skills or time. But spendings on machinery for example, will limit decision- and policymakers' future scope of action and might be unjustified whenever inefficiency is due to climatic conditions outside of the sphere of influence or due to farmers' conscious production choices (Hansson, Manevska-Tasevka and Asmild 2020).

Even though the effect of differing climatic conditions on the efficiency estimates is largely ignored, 'environment' and 'sustainability' are popular keywords to motivate nonparametric technical efficiency analysis. This is not limited to studies dedicated to eco- or environmental efficiency (e.g., He, Li and Cui 2021), but just as much includes traditional technical efficiency analyzes (e.g., Toma et al. 2017; von Hobe, Michels and Musshoff 2021). The latter are motivated by the prospect of learning about the harmonization of saving on scarce natural resources (inputs) on the one hand and satisfying the growing demand for food and fiber (outputs) on the other. From a conceptual point of view though, this rationale makes sense only if the technical efficiency estimate contains information on scarce natural resources and the provision of food and fiber. In the majority of the studies discussed above though, the technical efficiency model has been calculated employing land, labor, capital and often intermediate consumption as inputs, while farm gross output or another form of operational output serves as output. While in the input-oriented case, technical efficiency estimates might thus indeed to some extent reveal potential in savings on quantities of land, fertilizer, pesticides or energy, in the output-oriented case, they may above all reflect farms' or sectors' economic returns.

Partly, this convention could be explained by agricultural economists' interest in good comparability of studies in different empirical application cases or with previous analyses. Also, when analyses are conducted for cases that might only be of interest to a small, specialized part of the scientific community, agricultural economists might be interested in aligning their conceptual and methodological approach with acknowledged and frequently employed approaches. This seems likely given that the profound methodological advances in nonparametric analysis are in context of agricultural production only scarcely adopted thus far.[2] Regardless of the causes of the conventions lined out in this section, inadequate policy recommendations or erroneously motivating nonparametric analysis with sustainability goals should in any case be avoided. In this paper, we would like to contribute towards this goal by comparing the effect of regionally differing, determinate climatic conditions to conventionally employed contextual variables and proposing a conceptual alternative to the traditionally employed technical efficiency model with the approach introduced in the upcoming section.

[2] Substantial methodological advances have been made in the nonparametric methodology. Bădin et al. (2014) for example introduced a nonparametric conditional methodology, where a flexible location scale model is employed to regress the ratio of conditional to unconditional measure on external factors. Even though the methodology allows for the calculation of a pure managerial efficiency measure (, the residual of efficiency variation not attributable to external factors) thus far only two studies adopted the methodology in an agricultural production context. The study of Minviel and De Witte (2017) is the only analysis employing the methodology to agricultural efficiency in particular. (They did not consider environmental factors though, which is reasonable given their farm level scope.)

3 Methodology

3.1 Conceptual Model Decomposition and Hypotheses

Building on the remarks made in the literature review, the traditional technical efficiency model might in the input-oriented case indeed contain relevant information on the potential of resource savings. In the output-oriented case though, information on expansion of physical produce might be quite limited, given that conventionally an operational measure like farm gross results are employed as output variable. Further, a lot of the policy recommendations drawn by agricultural economists are directed at evaluating and enhancing efficiency caused by rather operational choices of decision-makers. We therefore suggest to conceptually decompose the technical efficiency model into two components. First, an (input-oriented) operational model containing all relevant cost variables linked to production inputs, which allows to make a judgment on the efficiency of input allocation. Building on an operational efficiency measure, policy recommendations like modernization and specialization might be justified and more targeted. Second, an (output-oriented) physical efficiency model, where the farm gross results are substituted by actual produce that contains all the information necessary for a making the judgment on harmonization of resource conservation and provision of food and fiber.

Since our criticism concerns the neglection of the impact of climatic conditions on efficiency estimates of the traditionally employed technical efficiency, the two introduced models will be compared to input- and output oriented (conventual) technical efficiency estimates. In a second step, we imitate the most frequently performed approach in the literature and incorporate a set of covariates representing sectoral characteristics into a second stage regression analysis. Of course, in our case we will also consider a set of environmental variables associated with crop yield variability, which we presume might translate to technical and physical efficiency of decision-makers. In case, we obtain a straightforward impact of environmental factors on technical efficiency estimates, the assumption H1a many studies implicitly build on will be rejected.

> H1a): Environmental factors do not have a statistically or economically significant impact on technical efficiency estimates.

Since our criticism included the prospect that a neglection of environmental factors could also lead to seriously misleading policy recommendations by wrongly attributing inefficiency to inefficient input-allocation, sectoral characteristics usually considered in the literature should play an economically subordinate role to environmental variables when explaining technical inefficiency. In this case, H1b needs to be rejected:

> H1b): Robustness of the statistical and economic significance of sectoral characteristics is not diminished by the inclusion of environmental variables as explanatory factors.

Second, in order to test whether technical efficiency and productivity measures reveal future potential for a harmonization of resource conservation and provision of produce, the physical productivity measure needs to actually increase over the considered period and coincide with the technical productivity index results. In order to support our claim that this is not the case, H2 needs to be rejected.

H2): Physical productivity has increased over the considered period and follows a similar trend as technical productivity.

3.2 Two-stage approach

Data Envelopment Analysis

In order to test hypotheses H1a and H1b, a two-stage approach is employed, which connects a radial Data Envelopment Analysis (DEA) model in the first step and a (censored) Tobit panel data regression model employing the yielded efficiency scores as dependent variable in the second step. Again, we are aware of e.g., the lack of a clear theory on the underlying data generating process when Tobit regression procedures are applied or that efficiency scores are not naturally independent observations but much rather serially correlated (Simar and Wilson 2007). Choosing a modified approach, building on an e.g., order-m or order-alpha frontier analysis adopting the nonparametric conditional methodology would solve those issues.

Yet, the credibility of our line of thought depends on guaranteeing for a good comparability of our empirical results with the results yielded based on the conventions we criticized in the previous section. Adopting a modified and less frequently employed methodology might reasonably cast doubt on the transferability of our findings to the findings of other studies. Further, we would also like to encourage the replication of our approach in order to allow for future considerations of environmental factors that is easy to implement. Given that authors, like Bădin et al. (2014) or Chambers, Pieralli and Sheng (2020), already explored the path of modified methodologies, we choose to adopt the conventionally used two-stage framework.

Based on the pioneering work of Farrell (1957) on production efficiency assessment, Charnes, Cooper and Rhodes (1978) were the first to introduce a linear programming technique, which allows to calculate relative efficiency scores of decision-making units considering multiple inputs and outputs. The mathematical formulations below reflect a reduced version of the DEA under variable returns to scale assumption, as first introduced by Banker, Charnes and Cooper (1984). Here the output-based radial efficiency scores are calculated as Debreu-Farrell measure of efficiency (Debreu, 1951; Farrell, 1957). Equation (1) denotes the production possibility set that describes the feasible technology T:

$$P(x) \equiv \{y : (x, y) \in T\} \tag{1}$$

of a specific production context in which all outputs y are producible by the inputs x. The upper boundary of the set defines the efficiency frontier, a convex hull that envelopes the empirically observed input-output ratios and is interpreted as the best-practice frontier of the sample. The distance of an individual DMU's output to the efficiency frontier (or its required proportional enlargement of output) determine a DMU's degree of technical inefficiency. The linear programming problem of the output-oriented DEA model corresponds to (Banker, Charnes and Cooper 1984):

$$\max \phi \tag{2}$$

$$s.t. \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{io} \; i = 1, 2, \dots, m;$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq \phi y_{ro} \; r = 1, 2, \dots, s;$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0$$

where the considered DMUo is one of n decision making units in the sample, for which the efficiency in transforming a set of m inputs into s outputs is evaluated. The empirically observed input and output quantities of DMUo are expressed by the vectors x_{io} and y_{ro} respectively. λ denotes the DMU's weight and ϕ its efficiency score. The linear program for the output-oriented case under constant returns to scale assumption coincides with equation (2) if the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$. is relaxed. The relationship of efficiency measured under constant returns to scale with efficiency measured under variable returns to scale reveals information on whether a decision-maker operates scale inefficient in the sense of operating on a scale section where the feasible technology is more restricted and only permits a lower level of productivity. The corresponding scale efficiency index can be calculated as $SE(o) = \phi_{CRS}(o)/\phi_{VRS}(o)$ (Arru et al. 2019).

Panel Tobit Regression Model

In the second stage, the determinants of the yielded efficiency estimates are assessed conducting a random effects panel data Tobit regression analysis. The yielded efficiency scores range in the interval [0,1] (with 1 = efficient, < 1 inefficient) for the input-oriented case and 1 (efficient) and > 1 (inefficient) for the output-oriented case. Employing a Tobit regression model to determine the relationship between inefficiency variation, contextual and environmental variables is believed to partly account for the input (output) -oriented efficiency measure being right (left) censored at 1, where the scores of the efficient DMUs are concentrated. Acknowledging the more fundamental methodological critique associated with two-stage analysis, this variant is expected to at least produce more meaningful results as e.g., an OLS based regression. A reduced version of the random effects panel data Tobit model is denoted by (Radovanov et al. 2020):

$$\begin{aligned} \phi_{it}^{*} &= x_{it}'\beta + \varepsilon_{it} \\ \phi_{it} &= 0 \; if \; \phi_{it}^{*} \leq 0 \\ \phi_{it} &= \phi_{i}^{*} \; if \; \phi_{it}^{*} \; \geq 0 \end{aligned} \tag{3}$$

where y_{it} is the dependent variable measured by y_{it}^{*} it as the latent dependent variable of the efficiency estimate according to efficiency model for positive values, otherwise censored, corresponding to region i and period t. The vector of independent covariates is denoted as x'_{it} with β being the coefficient vector and ϵ_{it} the error term, which is expected to be independently and normally distributed.

3.3 Malmquist-productivity index

Ideally, the validity of the conceptual decomposition of the efficiency model could be proven by employing the Malmquist-productivity index. In case, the technical productivity trend can be interpreted as product of the operational and physical productivity trend, future analyzes could simply incorporate the two proposed model set-ups to validify the implications of the technical efficiency model within their framework. This would allow for more refined policy implications allowing for a precise targeting of operational inefficiencies and productivity losses with some of the above criticized policy recommendations.

The Malmquist-productivity index (MPI) introduces by Caves et al. (1982) is an acknowledged method to account for trends in productivity when non-parametric methods are employed. The index values are calculated analogously to the DEA method based on distance functions, yet the decision-makers input-output combinations are not simply projected against the frontier of one period, but also against the production possibility frontier of a different base period. The Malmquist-Productivity Index thus accounts for the distance of inefficient decision-makers' input-output set to the production possibility frontier of a certain period t+1, relates this to the mean distance of DMUs to the production possibility frontier of a previous period t as well as relating the level of the production possibility frontier in t+1 to the one in t.

Based on an input vector $x^t = \{x_1^t, x_2^t, \dots, x_m^t\}$, and an output vector $y^t = \{y_1^t, y_2^t, \dots, y_n^t\}$, given the production possibility set $P^t = \{x^t,\ y^t\}$, the geometric mean of the Malmquist-Producitvity Index for t and t+1 corresponds to (Grifell-Tatjé and Lovell, 1994):

$$MP_t^{t+1} = [\frac{D_0^t(x^{t+1},\ y^{t+1}) D_0^{t+1}(x^{t+1},\ y^{t+1})}{D_0^t(x^t,\ y^t) D_0^{t+1}(x^t,\ y^t)}]^{\frac{1}{2}} \tag{4}$$

The index equals 1, if productivity remains constant. Values larger (smaller) than one indicate increasing (decreasing) overall productivity. Färe et al. (1994) further proposed to decompose the MPI into the technological and efficiency change component. The technological change measures the 'frontier-shift' and thus reveals differences in maximum feasible productivity over the considered time period. Values above one are believed to reflect positive technological development. For period t and t+1 it is defined as:

$$MPTECH_t^{t+1} = [\frac{D_0^t(x^{t+1},\ y^{t+1}) D_0^t(x^t,\ y^t)}{D_0^{t+1}(x^{t+1},\ y^{t+1}) D_0^{t+1}(x^t,\ y^t)}]^{\frac{1}{2}} \tag{5}$$

The efficiency change component in turn reflects how on average the distance of inefficient DMUs to the frontier develops. Values above one thus reveal the degree to which decision-makers are able to 'catch-up' to the most productive observations in the sample. For period t and t+1 it is denoted as:

$$MPEFFCH_t^{t+1} = [\frac{D_0^t(x^{t+1},\ y^{t+1})}{D_0^t(x^t,\ y^t)}]^{\frac{1}{2}} \tag{6}$$

For further details on the methodology of the Malmquist-Productivity Index see Caves et al. (1982), Färe et al. (1994) and Grifell-Tatjé and Lovell (1994).

4. Data

4.1. Efficiency model data

Technical efficiency

For the outlined approach, availability of data is crucial. For one, the conceptual decomposition of the traditional technical efficiency measure is only possible if data not only on conventionally employed inputs and outputs is available, but also data on input costs and explanatory factors. Further, the empirical application case should equally permit the integration of environmental data. In conjunction with the broad interest of agricultural economists in production efficiency, productivity and its determinants in the European Union, the EU's farming sector seems suitable as empirical application case.

Agricultural production data stems from the farm accountancy data network (FADN) database (2022) of the years 2004 to 2018. Farming sectors' representation of 122 regions (according to the FADN classification) classified as fieldcrops and mixed production farms are used. As outlined in the literature review, vulnerability of livestock specialists to climatic conditions might be limited and consequently they have not been taken up into the sample.

Technical efficiency (for both the input- and output-oriented case) will be computed with the (conventionally used) inputs land represented by the total utilized agricultural area (UAA) in hectare (SE025[3]), labor given as total labor input expressed in full time person working equivalents (SE010), capital as [€] value of the closing evaluation of total assets (SE436) and finally the intermediate consumption [in €] accounting for production specific costs such as seeds and seedlings, fertilizers, feed, other crop protection as well as overheads (SE275). The total output [€] (SE131), which denotes the monetary value of output of crops and crop products, livestock, and livestock products and of other input, including other gainful activities (OGA) of the farms, serves as the output of the technical efficiency model.

Operational efficiency

In order to decompose the traditional technical efficiency measure, the (input-oriented) operational efficiency will also be calculated with the total output as output and the intermediate consumption, which represents direct costs of production. The remaining inputs of the operational efficiency measure

[3] Reference number in FADN database. Detailed information on standard variables in the FADN database may be found here: https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

are included as the production costs tied to the classical inputs of technical efficiency.[4] The total labor input is thus substituted by the sum of wages paid (SE370) and spendings on contract (SE350) and contractual work (SE720). This includes wages, security charges (and insurance) of wage earners, as well as costs linked to work carried out by contractors. As equivalent to the land input serves the monetary value linked to maintaining and improving agricultural land (e.g., fencing, drainage and fixed irrigation equipment) (SE447). Finally, the capital input is substituted by capital costs, which we calculated as the sum of depreciation (SE360), balance of interest paid and received (SE381), balance of subsidies and taxes on investment (SE405) and net investment on fixed assets (SE521). We carefully considered dependencies of all variables to rule out potential redundancies.

Note that for a variety of regions, subsidies and interest received, result in negative aggregate capital costs, forcing us to exclude a considerable amount of observations from the sample (, since nonparametric analyzes do only allow for a consideration of positive integer numbers). The integration of the capital costs thus led to a reduction of sample size from 1,997 to 1,646 observations. This could potentially cause operational efficiency estimates to be biased, either positively because regions receiving high absolute amounts of subsidies could conduct business less intensive or inefficient, or negatively because higher amounts of interests received could signal a high long-term operational efficiency or simply benefits due to profitable investments in the past.

Physical efficiency

The second measure we are proposing as a supplement to the traditional technical efficiency model, is the physical efficiency model. In contrast to the operational efficiency measure, here in the (output-oriented case) the inputs of the technical efficiency model are taken over, while the total output will be substituted by physical outputs that contain the information that may allow to evaluate if actual produce is indeed expanded. Overall, three different physical outputs, wheat (SE110*SE025), maize (SE115*SE025) and milk (SE125*SE085) produce, which can be seen as proxy outputs for the production technologies of the crop specialists and mixed farming sectors in the EU, are considered. All three variables are given in absolute amounts in kilogram. Given the already high number of four inputs, limiting the output variables to three seems rational, to keep the share of efficient DMUs following an enlarged production set moderate.

Analogously to the operational efficiency model, the number of observations is considerably lower than for its technical efficiency counterpart, since data availability for actual produce is not available for all regions or at any point in time. In total, for the efficiency measure, sample size drops from 1,997 to 1,195 observations. Since availability of produce data also differed for individual regions within the time frame considered, the calculation of the Malmquist-Productivity index (, which requires data to be

[4] Note that in data envelopment analysis, the technical efficiency measure may also be decomposed methodologically into a cost and allocative efficiency measure if input quantities and prices are fully available. This approach is not adopted here since i.e., the total output considered is not simply calculated as output quantities multiplied by their price. Also, quantity data is not available for all inputs (e.g., intermediate consumption).

available for each region of all inputs, outputs and years) is based on a panel of 876 observations, thus posing the smallest sample size for any model within this paper. Similar to the operational efficiency model, the physical efficiency measure could thus be (, supposedly positively) biased since actual produce has been least consistently reported by eastern EU member countries. The latter have been found to be rather technically inefficient when compared to western member states (e.g., Błażejczyk-Majka, Kala and Maciejewski 2012; Kaiser and Schaffer 2022), which could cause structural differences in between the model samples.

Note that a comparison of mean efficiency estimates between the different models calculated with different data would in any case bear only very limited implications due to, e.g., differences in sample size, the enlarged size of the production set and thus differing shares of efficient DMUs (Bravo-Ureta et al. 2007; Minviel and Latruffe 2017). In line with our research issue, discussion of results will thus focus on model differences regarding the individual productivity trends and the explanatory power of the sectoral characteristics and environmental variables considered.

The presumed production dependency for the proposed models is supported by all inputs correlating significantly and strongly positive with the respective outputs (see Appendix S1 and S2 for a table showing correlations and significance levels). Descriptive statistics of the model inputs and outputs are given in table 1.

Variable	Obs.	Mean	Std. dev.	Min	Max
UAA [ha]	1,812	83.40	113.22	1.78	790.61
Labor [TLU]	1,812	1.98	1.86	0.40	20.99
Intermediate Consumption [€]	1,812	82,154.80	120,890.70	2,412.00	964,507.00
Total assets [€]	1,812	512,376.30	591,530.70	15,860.00	3,401,421.00
Costs UAA [€]	1,812	245,032.00	391,472.30	1,604.00	2,828,859.00
Costs labor [€]	1,812	26,006.82	50,074.67	200.08	401,567.30
Capital costs [€]	1,812	22,626.35	34,381.33	-79.944.00	293,590.00
Gross Output [€]	1,812	127,844.70	175,541.10	5,689.00	1,498,796.00
Wheat yield [kg]	1,696	5,466.845	7,978.05	31.72	53,631.51
Maize yield [kg]	1,474	7,436.677	10,904.55	106.05	141,200.50
Milk produce [kg]	1,514	44,001.65	101,145.30	0.00	858,638.40

Table 1. Descriptive statistics of model inputs and outputs.

4.1. Regression covariates data

Sectoral characteristics

In the literature, most contextual variables either refer to size, specialization, diversification, intensity or extensivity of practices and of course subsidization. A variety of authors assumes size to be beneficial for farms' efficiency due to increasing returns to scale (Forleo et al. 2021). Galluzzo (2016) argues for example, employing FADN data of Italian farms, that especially small-sized family farms' technical efficiency is low and largely dependent of subsidization. In order to incorporate the effect of size into the second stage of the analysis, we consider the economic size of a holding expressed in 1,000 Euro of standard output (SE005).

In our sample, crop specialized, and mixed production farm types are considered. Especially in context of the physical efficiency model, specialization could be decisive for the relationship of the partial productivities of crop yields and milk produce. Nonetheless, given that only the two farm types with migrating production technologies are considered, it might be useful to consider a continuous variable that accounts for the degree of specialization rather than considering the two farm types as dichotomous covariate. The number of dairy cows, expressed in livestock units (SE085), comprising all female bovine animals (including female buffaloes), which are held principally for milk production, thus serve us as specialization covariate.

Forleo et al. (2021) convincingly argued that apart from being an important factor in securing profitable incomes of family farms, diversification also influences farmers' technical efficiency. In line with previous studies (e.g., Arru et al. 2019), we therefore include other gainful activities (OGA) in form of total OGA output (SE700), related to the holding created i.e., from processing of farm products, receipts from contract work, agritourism, production of renewable energy or forestry.

To account for the intensity or extensivity of practices respectively, fertilizer quantities and agricultural area out of production are considered. The amount of purchased fertilizers and soil improvers (excluding those used for forests) (SE295) are considered as a proxy for rather intensive farming, whereas more agricultural area withdrawn from production (SE074), due to compulsory agricultural policy measures and permanent grassland and meadows no longer used but maintained in good environmental condition, are expected to reflect rather extensive farming practices.

Finally, in line with the majority of technical efficiency analyzes in agricultural production contexts (e.g., Minviel and De Witte 2017, Minviel and Latruffe 2017, Todorović et al. 2020), we consider the total subsidies on current operations linked to production (SE605), including subsidies on crops and livestock, total support for rural development, decoupled payments, as well as subsidies on intermediate consumption and external factors.

Environmental factors

Although only scarcely addressed in agricultural efficiency analyses, the dependence of European crop yield variability from climatic conditions is well documented (Supit et al. 2010). In our framework four environmental factors, namely radiation, temperature, precipitation and wind speed are accounted for. Note that the effect of climatic conditions on actual crop yield variability is much more complex that may be considered here on an aggregate annual and regional level. In crop yield variability studies, climatic conditions are frequently modelled non-linearly for different crop types individually and according to seasonal and spatial variations (Palosuo et al. 2011). For all of the considered variables there is an optimal corridor of values, which is beneficial to crop growth. Nonetheless, for the context of European crops, some assumptions regarding the potential aggregate effects of the environmental factors on technical efficiency can be made based on crop yield variability studies.

In context of European crop production, Peltonen-Sainio et al. (2010) find a negative effect of high temperature and precipitation levels on crop yield productivity. Heavy rainfall for example, can cause root rot or drowning of the crops. Hot and dry periods, especially in form of high maximum temperatures in summer, cause reduction of the growth of shoots, root growth and are also associated with lower wheat and maize yield productivity in European regions (Pirttioja et al. 2015; Zscheischler, Orth and Seneviratne 2017). We thus expect precipitation (given as annual mean of rainfall [mm]) and climate (represented by the mean annual temperature of each region [°C]) as unfavorable determinants of inefficiency.

High values of global solar radiation are known to enhance photosynthesis, which is responsible for sufficient accumulation of assimilates. Low levels of solar radiation lead to shortened grain filling periods and an increased risk of lodging. Mean total global radiation (in KJ/m2) is thus expected to be a positive determinant of a region's efficiency. (Guo et al. 2022)

While moderate wind speed alters the balance of hormones in crops and contributes to making carbon dioxide available to plants, wind erosion can be quite harmful, causing loss of plant nutrients, organic matter and changes in soil texture, which results in lower yield productivity. Mean wind speed [m/s] is thus included as fourth (supposedly unfavorable) environmental variable in the analysis (Lyles 1975; Fryrear 1985).

The four climatic variables are available as high-resolution point data derived from the Agri4Cast Resources Portal (European Commission 2022) and were extracted using a shape layer with the FADN classification of European regions. Finally, continuous annual means were calculated for all regions.[5] Extraction, cutting, and field statistics were performed using QGIS 3.14.

Descriptive statistics of sectoral characteristics and environmental regression covariates are given in table 2.

Variable	Obs.	Mean	Std. dev.	Min	Max
Global radiation [KJ/m2]	1,812	12,772.13	2,676.96	7,130.48	21,764.89
Temperature [°C]	1,812	11.87	3.40	-0.44	20.70
Wind speed [m/s]	1,812	3.04	0.83	1.32	5.71
Precipitation [mm]	1,812	1.85	0.58	0.11	4.27
Total production subsidies [€]	1,812	27,678.51	39,264.17	14.00	290,500.00
Economic size [€]	1,812	115.59	163.50	5.20	1,369.00
Area out of production [ha]	1,812	3.72	5.86	0.00	67.40
OGA output [€]	1,812	4,147.23	15,624.19	0.00	199,317.00
Fertilizers purchased [€]	1,812	11,451.09	16,350.24	122.00	125,666.00
Nr. of dairy cows [LU]	1,812	4.81	11.34	0.00	103.52

Table 2. Descriptive statistics of regression covariates.

[5] Please note that the climatic conditions thus refer to the total area of each region and are not agricultural area specific. Hence, weather events occurring on non-agricultural areas also partly constitute the environmental variables.

4 Empirical Results

4.1 *Two-stage approach*

Descriptive statistics of the efficiency estimates for the different models are provided in table 3.

Variable	Orient.	Eff. model	Obs.	Mean	Std. dev.	Min	Max
in_te_vrs	input	technical	1,812	0.87	0.11	0.42	1
in_te_se				0.86	0.16	0.21	
in_ope_vrs		operational	1,646	0.86	0.17	0.22	1
in_ope_se				0.81	0.20	0.17	
oo_te_vrs	output	technical	1,812	1.28	0.37	1	4.67
oo_te_se				1.13	0.29		4.83
oo_phy_vrs		physical	1,195	1.12	0.20	1	2.49
oo_phy_se				1.11	0.23		3.15

Table 3. Descriptive statistics of input- and output-oriented technical, operational and physical efficiency model estimates under variable returns to scale assumption (vrs), as well as scale efficiency estimates (se).

Looking at the input-oriented models, operational (scale) efficiency is found to be lower than technical efficiency. Analogously, for the output-oriented models, the EU farming sectors are less physically (scale) than technically (scale) efficient. For the different models, estimates of the Tobit regression analysis are given in table 4. First of all, we find the environmental factors radiation, temperature and precipitation to have a statistically and economically significant impact on the physical, the input-oriented and output-oriented technical efficiency models. Signs of covariates are consistent over all three models[6] and correspond to the expected effect based on the literature. Only exception is the variable wind, which reveals inconsistent results, suggesting a positive effect on both technical efficiency models, yet a negative impact on operational efficiency.

Also, wind speed is found to be statistically insignificant for the physical efficiency model. From a conceptual point of view this does not seem plausible since physical efficiency should be most vulnerable to all environmental factors. This suggests that the variable is quite sensitive to the model set-up and leads us to the conclusion that its results should be interpreted carefully.

The latter means that as expected there is no or only a quite moderate effect of environmental variables on operational efficiency. Indeed, our results suggest that operational efficiency largely depends on contextual variables regularly considered in the literature. Apart from the agricultural area excluded from production, all covariates are statistically significant. A higher number of dairy cows is found to be beneficial for profitability (in our sample of crop specialists and mixed farms), while engaging in other gainful activities and receiving more subsidization might signal that farmers either willingly conduct their business more extensively or are inadvertently less input allocation efficient. Quite surprisingly though, larger economic size and quantities of fertilizers have a negative impact on operational efficiency.

[6] Please note that for all output-oriented models the sign of the effect has to be the opposite as for the input-oriented models since in the output-oriented case >1 denotes inefficiency, while in the input-oriented case 0 to < 1 denotes inefficiency.

Table 4. Panel Tobit regression analysis results for input- and output-oriented technical efficiency, input-oriented operational efficiency and output-oriented physical efficiency model under variable returns to scale assumption.

ϕ_{it}^{vrs}	input-oriented		output-oriented	
	technical	operational	technical	physical
	(1)	(2)	(3)	(4)
Global radiation	2.18e-05*** (5.03e-06)	-1.36e-06 (6.28e-06)	-5.79e-05*** (1.78e-05)	-3.20e-05* (1.70e-05)
Temperature	-0.015*** (0.004)	0.005 (0.004)	0.041*** (0.013)	0.048*** (0.013)
Wind speed	0.035*** (0.009)	-0.034*** (0.011)	-0.115*** (0.032)	0.116 (0.032)
Precipitation	-0.020*** (0.007)	-0.004 (0.010)	0.058** (0.028)	0.070*** (0.025)
Economic size	9.32e-05 (7.08e-05)	-1.01e-04** (8.85e-05)	-8.64e-04*** (2.67e-04)	1.31e-04 (2.20e-04)
Area out of production	-0.004*** (0.001)	-7.72e-05 (0.001)	0.010*** (0.003)	0.001 (0.003)
Fertilizers purchased	-1.07e-06 (6.53e-07)	-1.92e-06*** (7.35e-07)	9.08e-07 (2.46e-06)	9.79e-08 (2.52e-06)
Nr. of dairy cows	0.003** (0.001)	0.006*** (0.001)	-0.003 (0.004)	-0.008** (0.004)
Total production subsidies	1.65e-07 (3.82e-07)	-1.53e-06*** (4.86e-07)	-1.70e-07 (1.42e-06)	-1.80e-06 (1.30e-06)
OGA output	2.73e-07 (2.49e-07)	-4.54e-07* (2.36e-07)	-9.33e-07 (9.73e-07)	7.74e-07 (8.43e-07)
constant	0.727*** (0.068)	1.011*** (0.078)	1.756*** (0.000)	0.707*** (0.237)
Log likelihood	947.93	708.80	-814.90	-267.58

*Note: ***, ** and * denote significance at 1%, 5% and 10% level.*

Partly, this could be due to the calculation under variable returns to scale, which to some extent offsets size-related differences. Thus, the negative effect of fertilizers could be interpreted as such, that operational efficiency is lower for farms of relatively comparable size (, occupying the same scale section), when they use larger quantities of fertilizers. Potentially, the peers constituting the different scale sections are regions characterized by farms of comparably smaller economic size, which spend less on input quantities. Yet, the effect of economic size is found to be statistically significant in the operational and output-oriented technical efficiency model exclusively. Assuming its effect to be meaningful, it is limited to the models that are neither associated with the harmonization of resource savings nor provision of food and fiber.

Comparing the results of the operational with the input-oriented technical efficiency model, a few things should be noted. First of all, apart from the number of dairy cows and the share of land excluded from production, no variable representing sectoral characteristics is found to have a statistically significant effect on input-oriented technical efficiency when environmental factors are considered. The negative effect of land excluded from production seems plausible given that the efficiency measure is partly based on total utilized agricultural area. The higher the share of UAA excluded from production, the lower the partial productivity of the land employed. In accordance with the findings for operational efficiency, mixed productions farms' efficiency might benefit from a higher share of livestock. An effect of size, fertilization or subsidization on the other hand cannot be found.

For the output-oriented models we find similar results for the sectoral characteristics. While in the technical efficiency model economic size and agricultural land excluded from production have a statistically significant negative effect on efficiency, in the physical efficiency model the only non-environmental factor that is statistically significant is the number of dairy cows, which is supposed to contribute to milk produce productivity. Thus, the results of the physical efficiency model suggest that physical produce substantially depend on environmental factors outside of the sphere of influence of the decision-maker. Nonetheless, it should be critically noted that we would have expected agricultural area out of production to have a profound effect on physical efficiency. Especially since it was found to have a statistically significant effect in the other output-oriented model.

It stands out that the interpretation of the conventional covariates is not always straightforward due to their statistical significance and signs of effects changing across the considered models. On the contrary (except for the variable wind speed), the interpretation of the environmental variables' effects is quite straightforward. Indeed, their varying economic significance according to efficiency model is also reasonable. As expected, we find higher coefficients for environmental variables in the physical efficiency model than in the output-oriented technical efficiency model. In conjunction with the higher standard deviation and maximum value (0.37 and 4.67 compared to 0.20 and 2.49) we conclude that the economic significance of environmental factors is more pronounced for the physical than the technical efficiency measure.

Given the Farrell-Debreu measure of efficiency, the interpretation of the coefficients might be most graphic for the input-oriented technical efficiency. Given all other model parameters stay constant, a change of one degree in mean temperature or one mm of precipitation could account for 1.5 or 2 percent of the efficiency estimate respectively. A change of global radiation of 1,000 KJ/m2 would in turn explain 2.2 percent of inefficiency. Given a mean efficiency of 0.87 and taking into account that in the sample temperature ranges from 0.44 to 21 degrees Celsius (3.40 std. deviation), precipitation from 0.11 to 4.27 mm (0.58 std. deviation) and radiation from 7,130 to 21,764 (2,677 std. deviation), the results suggest that environmental factors do not only have a statistically significant but also economically significant effect on agricultural production efficiency.

4.1 Malmquist productivity results

Descriptive statistics for the Malmquist-productivity index results are provided in table 5.

Variable	Prod. model	Obs.	Mean	Std. dev.	Min	Max
MP_te	technical	1,456	1.10	0.21	0.50	2.39
TECH_te			1.07	0.17	0.67	1.88
EFFCH_te			1.03	0.17	0.41	1.92
MP_ope	operational	1,091	0.98	0.21	0.36	2.39
TECH_ope			0.93	0.17	0.47	2.44
EFFCH_ope			1.06	0.21	0.51	1.98
MP_phy	physical	742	0.92	0.14	0.52	1.95
TECH_phy			0.91	0.12	0.61	1.42
EFFCH_phy			1.01	0.11	0.58	1.90

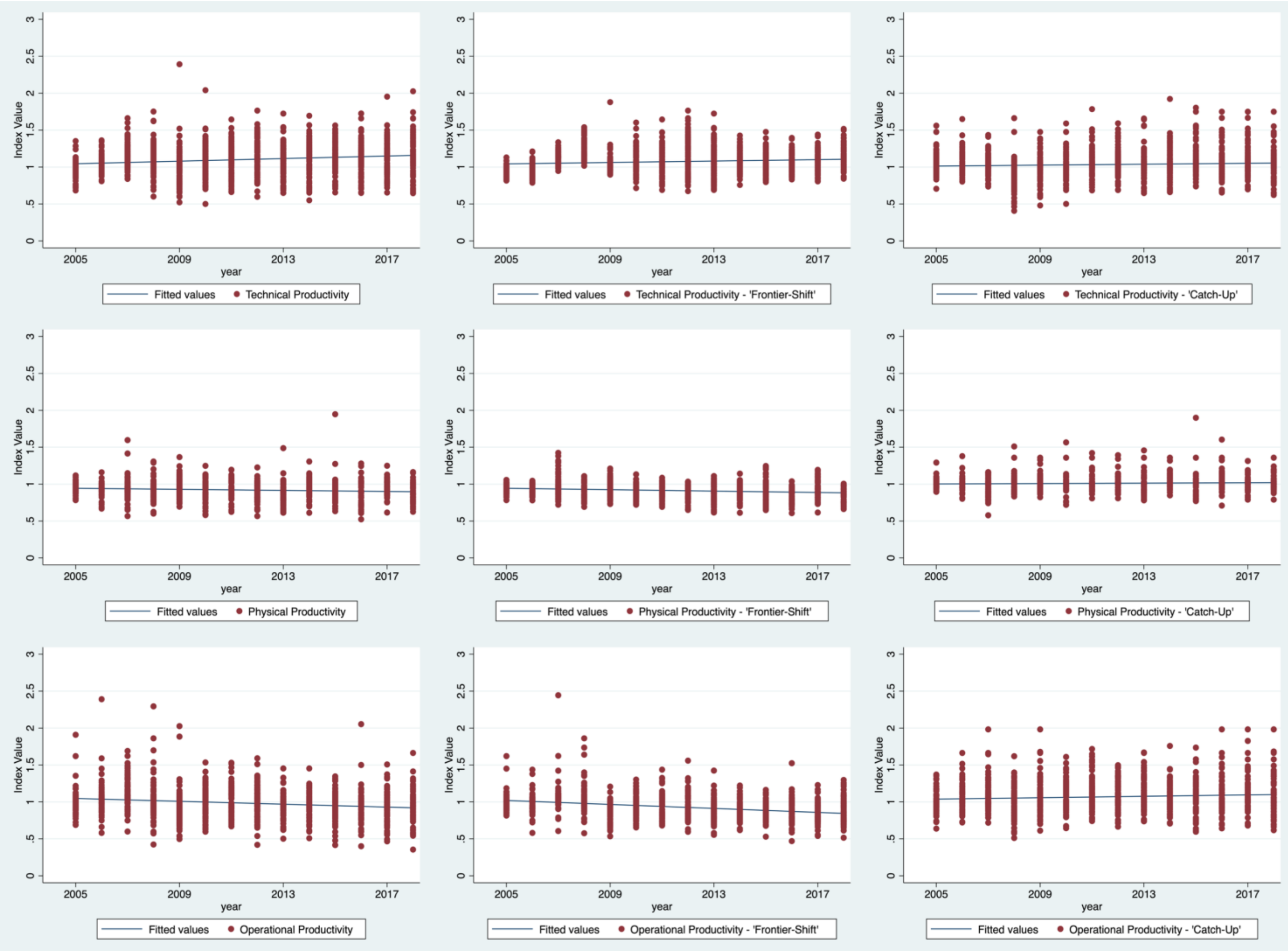
Table 5. Average Malmquist-productivity index (MP), technological (TECH) and efficiency change (EFFCH) component value for technical, operational and physical productivity of the period 2005-2018 (base year = 2004).

The results of the Malmquist-productivity index support the findings of the efficiency analysis. Looking at figure 1, we can obtain that the distribution of operational and technical productivity figures is quite wide whereas the variation of physical productivity estimates is rather narrow.

This suggests that for operational productivity the potential for productivity gains is in principle high. Nonetheless, over the considered period it has rather stagnated and on average sample peers have even become about 7 percent less productive (negative technological change). The stagnating overall trend in operational productivity thus stems from a substantial positive efficiency change effect, meaning that less productive decision-makers have ‘catched up’ to the frontier, indicating a more efficient allocation of production inputs.

In accordance with the findings for physical efficiency estimates, the range of physical productivity values is narrow when compared to the other models. The decline in mean technological change to about 0.91 suggests that substantial physical productivity gains due to induced technological change are rather unlikely. Overall, physical productivity has on average decreased of about eight percent, meaning that less productive regions have at least moderately catched up to sample peers.

Figure 1. Fitted and index values according to years for the Malmquist-productivity index, technological and efficiency change component



For our sample, technical productivity is the only model in which we obtain mean productivity gains of about 10 percent, driven by a significant frontier-shift of 7 percent and a moderate catch-up of 3 percent. Interestingly, the results indicate that the idea of viewing the operational and physical productivity measure as decomposed parts of traditional technical productivity must be rejected. This could be due to the above-mentioned lower comparability of the indices caused by the substantially reduced sample size and thus potential biases.

In any case, the results clearly show that physical productivity has decreased and only reveals a low potential for future productivity gains. For the considerably reduced samples, we find that the trends in physical and operational productivity are negative over the considered period and counteract the productivity gains measured with the traditional technical efficiency model.

4.2 Discussion

Our results only partly confirm the findings of previous studies assessing determinants of technical efficiency. While in the output-oriented case, economic size has a positive effect on efficiency, this cannot be confirmed for the input-oriented case. We find that our covariate representing extensivity is found to have a negative impact on efficiency. Indeed, and in contrast to findings of previous studies (e.g., Galluzzo 2018; Newman and Mathews 2007), we even find a negative effect of specialization (on crop farming) at least for the input-oriented case. Furthermore, the effect of covariates employed to account for diversification, intensive practices, and subsidies on the traditional technical efficiency model is unclear.

On the contrary, all four environmental variables employed have a statistically and economically significant effect on technical efficiency. Since the variable wind speed seems to be rather sensitive given the results of the decomposed efficiency models, we conclude that global solar radiation, temperature and precipitation are important determinants of technical efficiency. As a consequence, we argue that H1a and H1b can be rejected.

Regarding the implications of efficiency models for the harmonization of resource savings and expansions of food and fiber, the findings of the productivity analysis reveal a mixed picture. It could be shown that environmental factors have the most pronounced effect on the physical efficiency measure, while being least important for explaining operational efficiency. Yet, we could not provide evidence that the technical productivity measure can simply be decomposed into an operational and physical model of productivity. Indeed, the product of trends in operational and physical productivity do not coincide with the trend in technical productivity. Even though the comparability of the models might thus be limited, the physical productivity trend is actually decreasing for the EU's regional agricultural production and period of 2004 to 2018. The latter clearly suggests that future enlargement of produce while simultaneously reducing resource input might be overestimated and in any case needs to be accounted for explicitly, whenever studies motivate technical efficiency or productivity analyses by sustainability goals. Hypothesis H2 can thus also be rejected.

As already pointed out, one major drawback of our analysis might be the differing data sets according to each model, which followed from excluding observations that were neither available for a specific region, inconsistently over time or in case of operational productivity incompatible with the Malmquist-productivity index method. The resulting trade-off, to either further limit sample size in the productivity analysis for all three models or to lessen comparability of the results should be critically noted and might partially explain why the productivity analysis does not support the idea of the conceptual decomposition. Another drawback that was mentioned above is the choice of the methodology, for which a variety of limitations are well-documented (see 2.). While we are confident that environmental factors indeed play a vital role in explaining inefficiency variation and that they are not subordinate to previously considered contextual variables, the validity of our remarks on the economic significance (and its precise extent) of individual covariates might indeed be impaired by the method's limitations.

5 Concluding remarks

Based on conventions within nonparametric regional agricultural production efficiency and productivity analyses, two research issues were examined. First, we questioned the validity of regularly formulated (, rather operational) policy recommendations such as e.g., modernization, specialization and acquiring managerial skills, to reduce inefficiency whenever environmental factors are not properly accounted for in the analysis. Our findings clearly indicate that in analyses with a regional scope, environmental factors are decisive in explaining inefficiency variation. This could be shown for the frequently assessed case of EU agricultural production, employing the most popular nonparametric framework. In addition, our results suggest that the effect of regularly considered contextual covariates used to motivate the above-mentioned policy recommendations is subordinate to the effect of regionally differing determinate factors. Whenever determinate factors, such as environmental conditions might be relevant due to a regional, inter-country or even global scope, but are not accounted for, regularly proposed policy recommendations could be arbitrary and their value for decision- or policy makers thus unclear.

This paper further tried to contribute to the literature by proposing a decomposition of the traditional technical efficiency model. We presumed that a careful choice of inputs and outputs could differentiate the information the technical efficiency model contains on operational and physical productivity. The results of the efficiency analysis support this line of thought, showing a lower (higher) sensitivity of the operational (physical) efficiency model to environmental variables when compared to traditional technical efficiency. Even though a conceptual decomposition of technical efficiency could not be validified by the results of the productivity analysis, basing policy implications on the findings of the operational efficiency model, might nonetheless allow to make justified claims about decision-makers' input allocation efficiency and help find best practices for future productivity increases.

Interestingly, while the trend of technical productivity was found to be moderately positive for the considered period, physical productivity decreased, hence casting serious doubts on the idea of an ongoing harmonization of resource savings and provision of food and fiber. In conjunction with the technical efficiency model containing only limited information on actual produce, we conclude that the second issue raised, whether conventional technical efficiency and productivity analysis should be motivated by sustainability goals, should be objected to.

Finally, we would like to encourage future analyzes employing any nonparametric approach to assess determinants of efficiency to include environmental variables into their framework. Accounting for the stochastic nature of agricultural production methodologically might be useful, yet not always fully get a grasp on the structural impact spatially varying climatic features have on technical efficiency. By avoiding these conventions of nonparametric efficiency and productivity analyzes, future studies could help decision-makers to indeed improve their input allocation efficiency with targeted policy implications, while avoiding to wrongfully attribute inefficiency due to climatic factors outside of their sphere of influence or their conscious and rational choices.

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Appendix.

S1. Pairwise correlation coefficients and corresponding significance levels for operational model inputs and outputs.

	Costs land	Costs labor	Intermediate Consumption	Capital costs	Gross output
Costs land	1				
Costs labor	0.33***	1			
Intermediate Consumption	0.37***	0.97***	1		
Capital costs	0.40***	0.87***	0.93***	1	
Gross output	0.38***	0.96***	0.99***	0.93***	1

*Note: ***, ** and * denote significance at 1%, 5% and 10% level.*

S2. Pairwise correlation coefficients and corresponding significance levels for physical model inputs and outputs.

	UAA	Labor	Intermediate Consumption	Total assets	Yield wheat	Yield maize	Milk produce
UAA	1						
Labor	0.85***	1					
Intermediate Consumption	0.94***	0.80***	1				
Total assets	0.64***	0.47***	0.74***	1			
Yield wheat	0.97***	0.77***	0.95***	0.71***	1		
Yield maize	0.92***	0.75***	0.90***	0.71***	0.92***	1	
Milk produce	0.88***	0.81***	0.92***	0.88***	0.88***	0.84***	1

*Note: ***, ** and * denote significance at 1%, 5% and 10% level.*