Considering Environmental Factors in Technical Efficiency Analysis of European Crop Production

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Abstract

Data Envelopment Analysis (DEA) is a popular tool to determine technical efficiency of agricultural production. One issue that arises in some nonparametric frameworks is the heterogenous endowment with determinate factors, such as agroclimatic conditions. Environmental factors clearly lie outside of the sphere of influence of the decision-maker and pose natural limits to increasing efficiency and productivity of agricultural production. Calls for rationalization or better allocation of production inputs might thus not be adequate if concerned studies do not properly account for exogeneous factors of efficiency. The presented paper addresses the existing attempts to deal with the issue and analyzes the effect of soil quality on technical efficiency, calculated for crop producers of 122 European regions (FADN), using a regularly employed two-stage DEA framework. The effect of soil quality is then accounted for by adjusting the input factor land by a land quality factor. First, results show that environmental factors, e.g., soil quality, have a significant positive effect on technical efficiency. Further, the proposed land adjustment reveals structurally different results for some individual efficiency estimates, which indicates that neglecting the effect of environmental factors on efficiency might yield misleading policy implications.

Keywords

technical efficiency; environmental factors; exogenous factors; nonparametric efficiency analysis; two-stage approach; land heterogeneity; crop production

1 Introduction

In FARRELL's (1957) pioneering work that paved the way for today's nonparametric efficiency and productivity methods (e.g., Data Envelopment Analysis (DEA), Malmquist Productivity-Index), US Agricultural sector data served as illustrative example for the efficiency calculation. Both author and reviewers emphatically emphasized the mere illustrative character of the results. Farrell argued that any attempt to *draw more than the roughest inferences about American agricultural efficiency* (FARELL, 1957: 266), would require for a detailed attempt to account for input heterogeneity caused by different climatic or fertility conditions of the analyzed regions (FARRELL, 1957).

Quite surprisingly, in the agricultural economics literature, plenty of studies on efficiency or productivity have since been published that do not account for input heterogeneity. Partially, this can be explained by differing application cases. Efficiency in analyses conducted on farm-level limited to specific, largely climate independent, farm types, e.g., dairy farming (PIERALLI et al., 2017), might as well be subject to input heterogeneity, yet the heterogeneity is caused by managerial differences and the resulting degree of (in-) efficiency is fully attributable to the decision-maker (KAISER et al., 2020). In application cases though, where nonparametric studies are conducted with either a regional, international, or worldwide scope, input heterogeneity may arise due to exogenous factors outside of the sphere of influence of the decision-making units (DMU), e.g., environmental conditions as suggested by FARRELL (1957).

One crucial motivation for analyzing agricultural production efficiency and productivity on a broader scale, lies in determining the potential for global output expansion and input savings (VON HOBE et al., 2021). The former is often motivated by the rising demand for food caused by continuing population growth (DAGAR et al., 2021). The latter acknowledges the need for a more cautious use of natural resources in the future (CZYŻEWSKI and GUTH, 2021). Both issues concern a broader picture and cannot adequately be assessed with a local scope, e.g., on farm-level. Consequently, giving up on agricultural efficiency analysis, that is subject to heterogenous environmental characteristics, is not satisfying.

On the other hand, if input heterogeneity is not accounted for, the regularly formulated calls (e.g., GUESMI and SERRA, 2015; RUNGSURIYAWIBOON and WANG, 2009; TOMA et al., 2017) for better allocation of production inputs, specialization, modernization, or rationalization might not contribute towards expanding outputs and saving resources but much rather lead

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towards ignoring the naturally imposed limits on agricultural productivity, e.g., intensification of practices on already degraded soils.

This paper seeks to contribute to the literature by providing proof that existing approaches do not sufficiently cover the effect of input heterogeneity on agricultural efficiency caused by environmental factors. To achieve this goal, a regularly employed two-stage DEA framework is used to assess the effect of environmental conditions on crop production efficiency of 122 European (EU) regions. In a second step we account for the effect of significant environmental factors by adjusting the input factor land by an agricultural land quality factor. One considered environmental factor, soil quality, is found to have a robust and significant positive effect on technical efficiency. Also, the proposed land quality adjustment causes structural changes in the distributions of individual efficiency estimates. Since policy implications of nonparametric efficiency analysis are based on judgments of individual DMUs' potential for saving inputs or expanding outputs, our results suggest that they might be unreliable whenever exogenous factors are not accounted for.

The remainder of the paper is organized as follows. Section 2 briefly reviews existing approaches to consider environmental factors in nonparametric efficiency analysis. This is followed by methodological remarks on the two-stage nonparametric approach and the model description in Section 3. In Section four empirical findings are discussed. Finally, the paper closes with concluding remarks in Section 5.

2 Literature Review

The importance of considering heterogenous environmental conditions in agricultural production, productivity and efficiency analysis is well documented (BURKE and EMERICK, 2016; NJUKI et al., 2018; ZHAO et al., 2017). In fact, GARCIA-VERDU et al. (2019) just recently emphasized that agricultural production and thus the future development of agricultural productivity is among the most climate-sensitive areas within economics. In the context of crop production, the complex relationship of production efficiency with climate-related growing conditions and agricultural practices is manifested in the quality of the agricultural land employed (BHALLA, 1988; JAENICKE and LENGNICK, 1999; TÓTH et al., 2013). Various studies on agricultural productivity or efficiency (not using nonparametric techniques) thus account for input heterogeneity and integrate land quality related factors into their analysis (e.g., FUSCO and VIDOLI, 2013; LIANG et al., 2017; LOBELL et al., 2011).

It is thus surprising that the majority of nonparametric efficiency and productivity analysis conducted on a regional (e.g., ALDAZ and MILLÁN 2003; BŁAŻEJCZYK-MAJKA et al. 2012; BAGCHI et al. 2019), inter-country (e.g., BUREAU et al. 1995; FULGINITI and PERRIN 1997; TRUEBLOOD and COGGINS 2003) or global scope (e.g., ATICI et al. 2018; BALL et al. 2001; COELLI and RAO 2005) for which the above-mentioned exposure to environmental factors applies, do not incorporate the effect of land quality into their frameworks.

MILLÁN and ALDAZ (1998) argued that the issue is likely to be resolved when improved measurement methods are available.[1] One notable example for such an improvement is the analysis of CHAMBERS et al. (2020). They performed a nonparametric productivity analysis for the period 1961 to 2004 and chose to construct different subsets of years to guarantee for what they define as a climatological normal in the analysis. They found weather-related shifts of the frontier to be an important determinant of productivity development in particular regions. While this approach is well-suited for accounting for weather-specific events, its applicability is limited to productivity analysis over extended time periods and land quality related effects cannot be considered. Also, in efficiency analysis (using cross-sectional data of one exclusive period) subsampling or clustering of DMUs with homogenous environmental conditions might not be compatible with the researcher's interest and will significantly reduce sample size.

A second notable example is the paper of BĂDIN et al. (2014), who introduced a nonparametric conditional methodology that could solve the problem as described above. The idea is to calculate two sets of

[1] Indeed, since then, a lot of useful methodological advances were made in nonparametric efficiency and productivity analysis. See RUGGIERO (1998) for a discussion of options to consider non-discretionary inputs with a two-stage framework. CAZALS et al. (2002), e.g., introduced outlier robust estimation techniques. SIMAR and WILSON (1999), e.g., proposed bootstrapping procedures to enable the calculation of bias-corrected efficiency scores and allow to construct confidence intervals for efficiency estimates. While those models and methods help to eliminate extreme observations and account for measurement errors or random effects, they cannot sufficiently account for structural effects on the level of the individual efficiency estimates (BĂDIN et al., 2014; GADANAKIS and AREAL, 2020).

efficiency estimates, a conditional set containing an exogenous factor and an unconditional one. In a second step 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 pure managerial efficiency (the residual of efficiency variation not attributable to external factors), the approach has not been adopted by researchers performing efficiency and productivity analysis of agricultural production.[2] One possible explanation could be that implementation and interpretation of the conditional methodology is complex for both researcher and reader, which might not be justified in cases where the research goal is to simply provide reliable judgments on efficiency, as opposed to analyzing in detail the quality of the impact of a specific exogenous factor. Also, up until now the methodology has not been adopted in a productivity analysis context. Another possible explanation could be that the importance of exogenous factors in explaining the inefficiency distribution is still not ubiquitously established among researchers dealing with either productivity or efficiency of agricultural production.

The most popular approach to partly consider environmental factors in nonparametric efficiency analysis is the so-called two-stage approach, which may be summarized as conducting either a censored or truncated regression analysis employing the calculated efficiency estimates as dependent variable (ZHOU et al., 2018). But providing statistical evidence that environmental factors have an impact on the mean efficiency of a sample does not improve the quality of the addressed policy implications, since they are not derived based on the mean efficiency of the sample but of the relative comparison of the actual individual efficiency estimates (e.g., NIAVIS et al., 2021; NOWAK et al., 2015; TOMA et al., 2017). Indeed, mean sample efficiency might only be of interest in very seldom cases, in particular meta-analysis (e.g., BRAVO-URETA et al., 2007; MINVIEL and LATRUFFE, 2017). Consequently, we argue that for most research interests finding determinate exogenous factors to have a significant effect on the efficiency estimates, renders an interpretation and formulation of policy implications difficult. A nonparametric two-stage approach can thus not sufficiently account for the effect of land heterogeneity in analysis of agricultural production efficiency and productivity. A meaningful interpretation could only be guaranteed if the effect were to be distributed evenly across all DMUs. The latter is verifiable by the methodology employed in this paper, which will be outlined in the upcoming section.

3 Model Setup

3.1 Nonparametric Efficiency Analysis

Traditional DEA has emerged as one of the most popular instruments to identify efficiency boundaries of farms or regional agricultural systems. The mathematical formulations below reflect a reduced version of this approach that is described in full detail by DARAIO and SIMAR (2007). Presuming that farms improve their efficiency more likely by growing outputs rather than decreasing inputs, we calculate output-based radial efficiency scores. Equations (1) to (3) set up the traditional model which serves as a starting point for our analysis.

The productive organization of farms (or in our case average farms of the considered regions) can be denoted by a production set Ψ as:

$$\Psi = \{(x, y) \mid x \in R_+^p, y \in R_+^q, (x, y) \text{ is feasible}\} \tag{1}$$

where x is the input vector consisting of a set of inputs p, and y is the output vector consisting of a set of outputs q. If a DMU is capable of obtaining outputs q from the employed inputs p the production set is considered feasible. In radial terms the efficient boundary in the output space of the sections of Ψ can be defined as:

$$\delta P(x) = \{y | y \in P(x), \lambda y \notin P(x), \forall \lambda > 1\} \tag{2}$$

where $P(x)$ refers to the output correspondence set (for all $x \in \Psi$). In our framework the efficiency measure bases on the Shepard distance function (instead of the Debreu-Farrell measure of efficiency (DEBREU, 1951; FARRELL, 1957)), which provides a normalized measure of Euclidean distance from a

[2] Of the 147 citations of the paper documented on google scholar, only two articles treat of agricultural production in a broader context. Most applications concern efficiency in the public sector (water industry, public health, higher education institutions). The study of MINVIEL and DE WITTE (2017) is the only study to adopt the methodology in an agricultural efficiency context, but without considering environmental factors, which is reasonable given their analysis' interest lies in examining the effect of public subsidies and is based on farm level data.

point $(x,y) \epsilon R_{+}^{p+q}$ to the boundary of Ψ in a directional orthogonal to x:

$$\vartheta^{out}(x,y) = \inf\{\lambda > 0 | (x, \lambda^{-1} y) \epsilon \Psi\} \equiv (\lambda(x,y))^{-1} \quad (3)$$

where for all $(x,y) \epsilon \Psi, \vartheta^{out}(x,y) \leq 1$. For the case that $\vartheta^{out}(x,y) = 1$, then a region to which the input-output combination (x,y) belongs is technically efficient and constitutes the efficiency frontier (DARAIO and SIMAR, 2007).

In our framework the analysis is limited to the crop farming sector, which is regularly incorporated in inter-country analyses (COELLI and RAO, 2005). Also, we assume the effect of environmental variables on efficiency to be more pronounced here than for farms predominantly obtaining its gross output, e.g., from livestock farming. The input-output system is reproduced by variables commonly employed in the literature to describe the agricultural production process. The latter is constituted by agricultural land x_l and other manageable inputs x_i, such as labor, capital, and an intermediate input on the input- and gross production (in €) on the output-side (model 1).

In a second model, we consider that efficiency estimates also depend on the impact of exogenous factors on the production process. If those factors were manageable, it would be reasonable to include them as inputs, outputs, or detrimental outputs directly into the input-output system. However, as FARRELL suggested, for the case of agricultural production, determinate exogenous factors might above all be environmental conditions a farmer (or region) is facing that cause input heterogeneity unalterable by the decision-makers.

Along this line of though some authors (outside of the nonparametric efficiency analysis literature) propose to adjust agricultural land by means of the physical conditions, for example by introducing the concept of effective land (BHALLA, 1988). A land quality index could be used to reflect the endowment of a considered region with production-related environmental conditions. In this case the calculation of crop production efficiency ϑ is based on effective land x_{l_e} (rather than x_l) and other manageable inputs x_i (model 2), where effective land x_{l_e} can be considered a function of utilized cropland x_l and land quality s:

$$x_{l_e} = F(x_l, s) \quad (4)$$

3.2 Truncated Regression Analysis

Clearly, the consideration of land quality must be implemented carefully. As outlined above, the two-stage framework is the most popular tool to assess the effects of exogenous or environmental variables on the efficiency of a considered sample. We will follow this procedure to examine the effect of a bunch of potentially relevant environmental variables and apply a truncated regression model (5) based on a bootstrap technique as proposed by SIMAR and WILSON (2007)[3]:

$$\vartheta_i^{out} = s_i \alpha + z_i \beta + \varepsilon_i \quad (5)$$

where ϑ_i^{out} is the efficiency of DMU (region) i, s_i the soil quality in region i, z_i a set of control parameters (other determinate factors such as precipitation, climate or topography), α, β the regression coefficient reflecting the impact of the determinate factors on efficiency and ε the error term. The error term ε is now assumed to be statistically independent across DMUs and to be normally distributed with a two-sided truncation (for our case of the Shepard efficiency measure).

3.3 Adjustment of Agricultural Land

If regional differences in technical efficiency are indeed driven by environmental factors, results of conventional analyses could be misleading. In particular it might not be in the scope of farmers' decisions to increase efficiency sustainably. Instead, lower efficiency could be explained by comparatively unfavorable physical conditions of agricultural land. For this reason, we suggest to account for land heterogeneity by adjusting agricultural land accordingly and to recalculate efficiency with modified inputs in a second step (Model 2).

Weighting agricultural land, in order to, e.g., differentiate regional soil fertility and allow for better comparability, is quite common. Consider, for example, the application of yield and equivalence factors on (crop-)land within the frame of ecological footprint

[3] SIMAR and WILSON (2007) convincingly argue that statistical inference of analysis based on simple OLS or censored (Tobit like) regression procedures is questionable because of the lack of a clear theory on the underlying data generating process and neglecting that the efficiency scores are not naturally independent observations but much rather serially correlated. The estimation was conducted using the STATA package by BADUNENKO and TAUCHMANN (2019) employing algorithm 1 calculating regular Shepard efficiency scores.

analysis or the transfer of land (in ha) into so-called yield index units (*Ertragsmesszahlen*) by accounting for soil and agro-climate conditions in order to ensure a fair land tax distribution in Germany. BHALLA (1988) introduced an approach which constructs a land quality index based on regression results. However, those or similar procedures have not yet been applied in the context of non-parametric efficiency analysis. Following this line of thought, we weight the factor land on the basis of region i's land quality in relation to the average land quality of the full sample (6):

$$x_{l_e,i} = x_{l,i}\frac{s_i}{\bar{s}} \tag{6}$$

with $x_{l_e,i}$ being the effective land of an average farm in region i, $x_{l,i}$ the utilized agricultural area, $s_i$the land quality in region i *and* $\bar{s}$ the average land quality of the whole sample. This means effective land just equals utilized agricultural area for regions with average land quality and it is higher (lower) for regions with soil quality above (below) average.

Clearly, this is a very rudimentary adjustment approach, where the relationship of agricultural area and land quality is described in a much more simplified manner compared to the above-mentioned calculation of global hectares within the frame of ecological footprint analysis or the calculation of the German yield index units. However, the consideration of effective land here is primarily considered to test whether technical efficiency analysis that accounts for soil quality or other determinate factors yields structurally different efficiency estimates for our empirical application in the context of regional agricultural production of the EU.

4 Empirical Application

4.1 Data

In line with most empirical studies in this field, considered inputs of the conventional technical efficiency analysis (Model 1) comprise utilized agricultural area, average labor input expressed in annual working units (TLU), capital in form of total assets and crop specific costs reflecting intermediate inputs such as seeds, plants, fertilizers, crop protection and other crop production related costs. Agricultural outputs are given as (regional average of the) total output (see Table 1 for details).

All data originate from the farm accountancy data network (FADN) database (2020) and refer to the year 2018. In total the analysis includes average farms of 122 regions (according to FADN regional classification) classified as *fieldcrops farms* (for representation of farms within sample, see Appendix S1.). The focus on cropping farms is due to the farms' stronger exposition to environmental factors and a better comparability of the production processes and applied technology.

Furthermore, in order to account for the effect of exogenous factors on efficiency estimates and replace the factor land by effective land in Model 2, we also consider three environmental variables, which presumably have a significant impact (not only on crop yields, but also) on the efficiency estimates of the regional crop production agricultural sectors.

Previous nonparametric studies employing a (two-stage procedure) have found that productivity of the manageable inputs and therefore technological efficiency (DAI, 2013; NOWAK et al., 2015; TÓTH et al., 2013; ZAMBRANO et al., 2018; ZHAO et al., 2017) is influenced by soil quality. The soil biomass produc-

Table 1. Descriptive statistics

Obs. = 122	Name	Mean	Std. Dev.	Min	Max
Input	UAA [ha]	87.62	90.60	3.22	484.19
	TLU [AWU]	1.70	1.00	0.46	7.18
	Total Assets [€]	577,816	679,116	47,455	3,650,151
	Specific Crop Costs [€]	33,897	33,642	3,776	191,629
Output	Gross Output [€]	122,947	116,956	14,252	660,196
Exogenous Factors	Temperature [°C]	12.63	3.17	1.69	20.73
	Precipitation [l/mm]	1.82	0.57	0.44	3.16
	Soil Quality [Index]	5.92	0.94	3.79	8.10

Source: own calculations

tivity index of croplands provided by the EUROPEAN SOIL DATA CENTRE (2022) and TÓTH et al. (2013) accounts for the geographic location (climatic, hydrological and terrain conditions), soil physical properties, chemical properties and soil depth. Further, the index contains crop production specific information on the capacity of soil to supply nutrients, for water-storing and as a rooting medium for plants. The Index values range from 0 (low productivity potential) to 10 (high). If environmental factors have a substantial impact on overall efficiency of a region this should be reflected by its mean soil quality index value. Furthermore, we'd argue that a soil quality index is a good fit with our proposal to adjust for land heterogeneity with a land quality factor in Model 2.

Since environmental factors apart from land quality might also explain efficiency variation, e.g., due to weather-related events like local or temporal drought, heat or frost periods, we further control for robustness by considering two more agroclimate factors, precipitation and climate conditions, which are known to have an impact on crop yields productivity and variability. (DAI, 2013; NOWAK et al., 2015; TOTH et al., 2013; ZAMBRANO et al., 2018; ZHAO et al., 2017). Indeed, for European regions a favorable combination of rainfall and temperature can explain a large quantity of crop yield variability (e.g., about 72% for maize yield). Since we believe the latter to also potentially have an impact of efficiency of crop producers, we consider precipitation as annual mean of rainfall (in mm) and climate represented by the mean annual temperature of each region (in degrees Celsius) as covariates. Both agroclimate variables stem from the EU Agri4cast Resources Portal (EUROPEAN COMMISSION, 2020). Of course, annual means might not be sensitive enough to represent the complex and local relationship of the growing season of each individual crop, region and rainfall or temperature data in detail (MERONI et al., 2017). We suppose though it might constitute a good indicator to account for extreme weather-related events that part from the general endowment with climatic conditions reflected by the soil quality index.

All three determinate variables are given as high-resolution point (precipitation, mean temperature) or raster layer data (soil quality) and were extracted using a shape layer with the FADN classification of European regions. Afterwards continuous annual means were calculated for each region individually.[4] Extraction, cutting, and field statistics were performed using QGIS 3.14.

Descriptive statistics of all variables introduced in the sections above are given in Table 1.

4.2 Model Results

Technical Efficiency Results (Model 1)

Starting with the familiar Model 1, we calculate technical efficiency scores under variable returns to scale for the 122 regions (or more precisely the average regional farms) without consideration of land quality. Efficiency scores range between 0.44 and 1 with a mean of 0.82 and a standard deviation of 0.15. Results for the regions individual efficiency scores are listed in Table S1 and plotted in Figure 1.

Not surprisingly and in line with former empirical studies, the findings indicate relatively high technical efficiency scores for the Western and Central European countries. This is particularly true for regions characterized by highly intensive agricultural systems along the Coastline of the English Channel and the North Sea (e.g., Hauts de France, Vlaanderen, Netherlands, Lower Saxony, Denmark), but also holds for other regions in France, Belgium, Germany, Austria or Northern Italy. In contrast, comparatively low technical efficiency scores can be observed for North-eastern and Southern countries such as Poland, Lithuania, Scandinavia, Italy, the Baltic States or large parts of Spain. Thus, to some extent we can confirm the often-cited core-periphery divide in terms of efficiency among the EU member states with a general divide between Northern or Western countries on the one side and Southern or Eastern countries on the other (BARÁTH and FERTŐ, 2017; BŁAŻEJCZYK-MAJKA et al., 2012; NOWAK et al., 2015).

However, there are notable exceptions from this rule. In particular we find rather high efficiency scores for peripheral regions in Poland, Slovakia and the South-East (Romania, Bulgaria, Greece). This can partly be explained by the expansion of intensive farming practices towards peripheral regions (e.g. in Slovakia) but it also relates to the calculation of technical efficiency under variable returns to scale. Following this approach, some (South-Eastern) regions could constitute the efficiency frontier, even if they might be absolutely less productive than other (Western) regions (for example if lower yields per hectare

[4] Please note that the environmental factors thus refer to the mean of the total area of each region, not the specific area employed for agricultural production. Potentially, weather events occurring on areas subject to different land use could deter the environmental variables.

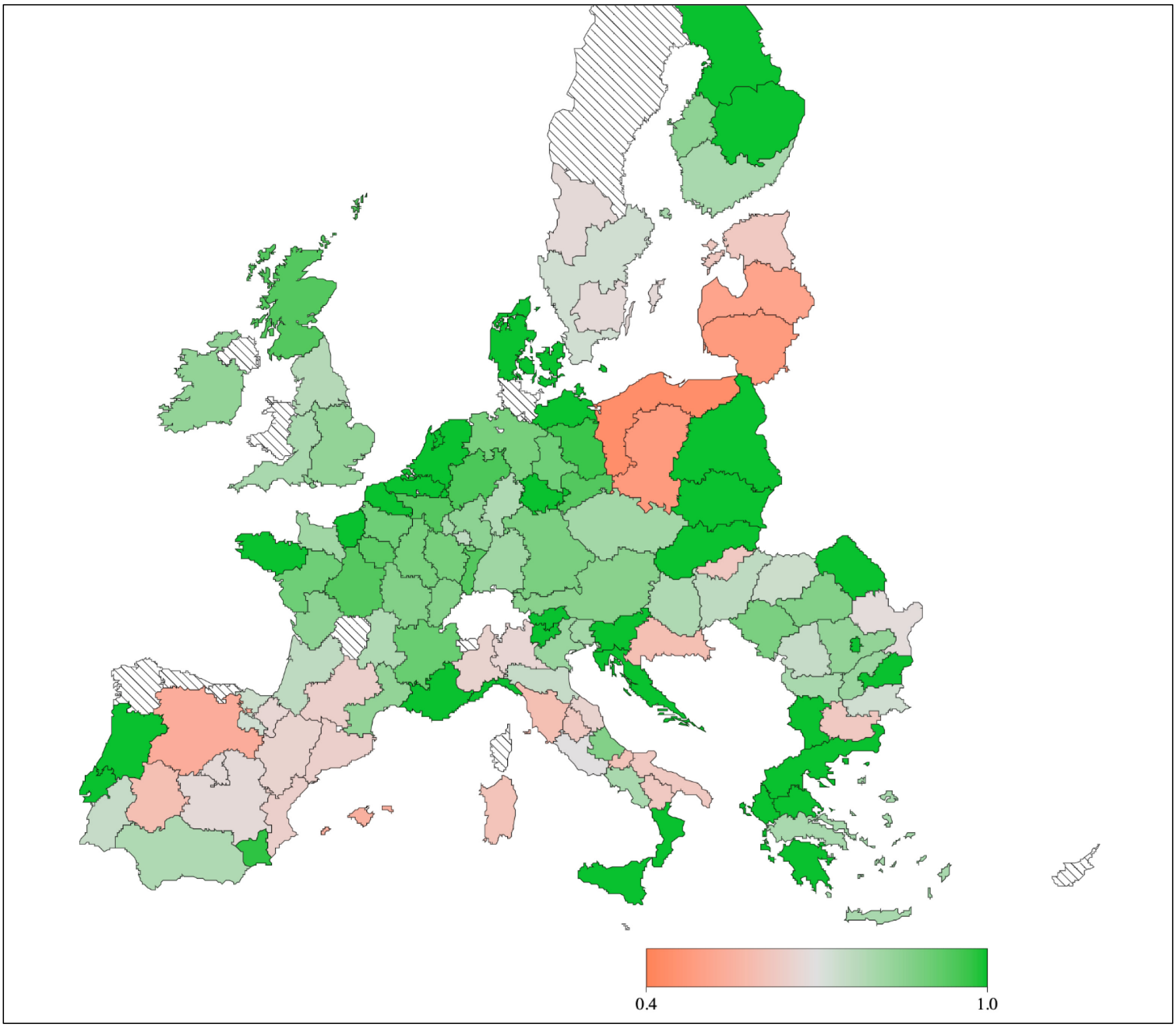
are produced with comparatively smaller use of input factors), yet relatively productive given the scale section they are occupying.

The broad range of agricultural systems in Europe, from very intensive production systems to low-intensity, traditional or organic farming has a long history and certainly reflects different institutional settings, farm characteristics and ideas about agricultural production. In addition, and maybe most important, yield productivity and farming practices rely on soil quality, topography and agroclimate conditions. While highly intensive farming practices can generally be observed on more fertile land, organic and other low-intensity farming are more common on land with poorer soil quality.

Technical Efficiency Results considering Land Quality (Model 2)

However, differences in soil quality and other determinate factors might not only affect yield productivity and farming practices but, following the discussion in Section 2 and 3.2, also technical efficiency. More (less) fertile land, for example, can be expected to increase (decrease) productivity of other inputs and therefore affect technical efficiency in a positive (negative) way. For this reason, the conventional efficiency scores (Model 1) are regressed on soil quality according Equation (5) in a next step. To avoid that soil quality reflects the effect of various determinate or unobserved factors, we further control for precipitation and climate, which are regularly considered to

Figure 1. Distribution of technical efficiency scores (Model 1) across European regions



Source: own illustration

explain crop yield variability and could thus have an impact on farm gross output results (DAI, 2013; MERONI et al., 2017; ZAMBRANO et al., 2018).

First results confirm the proposed robust, significant and positive impact of soil quality on technical efficiency.[5] This is in contrast to precipitation and mean temperature, which have no robust significant impact on technical efficiency (Table 2). As outlined above, the variables calculated based on annual means could indeed be too insensitive to get a grasp around the relationship of crop growing conditions, climate and precipitation. On the other hand, the efficiency estimate cannot be assumed to have an identical relationship with environmental factors like crop yields. In fact, their effect on a composite efficiency indicator might just be negligible. Against this background, the next step is to calculate the adjusted land variable according to Equation (6), incorporating the soil quality index as sole determinant of land quality, in order to recalculate technical efficiency with modified inputs. Following this approach efficiency scores increase, if crop production is limited by comparatively low soil quality and they decrease for regions endowed with high soil quality. In both cases, the adjustment process (partly) compensates for the more difficult or favorable biophysical conditions. Of course, efficiency could remain unchanged despite the

Table 2. Impacts of exogenous factors on technical efficiency according to model 1

VRS	Observed Coefficient	Percentile 95% Confidence Interval	
Soil Quality Index	0.048** (.0199)	.0101	.0884
Precipitation	0.018 (.0332)	-.0439	.0826
Temperature	-0.001 (.0070)	-.0146	.0121
Constant	0.476*** (.1744)	.1325	.8206
Sigma	0.1356*** (.0139)	.1074	.1625
Wald chi2 (3)	9.15**		

Note: ***, ** and * denote significance at 1%, 5% and 10% level. Std. Bootstrap Errors in parenthesis
Source: own calculations

land adjustment procedure. For example, if soil quality is close to average and fertility of land no major issue (neither in a positive nor negative way). Also, the efficiency measure is bounded at one for all regions that are found efficient in Model 1. Though many of these efficient regions dispose of highly fertile land, they could still define the efficiency frontier and remain efficient after the adjustment. After all soil quality might not be the decisive factor for those highly efficient regions, often characterized by rather intensive farming practices.

For efficiency estimates calculated according to Model 2, changes in mean technical efficiency are close to zero (0.004). Of 122 observations only 27 efficiency scores were affected by the consideration of soil quality. Figure 2 illustrates the differences between the revised technical efficiency scores (with adjusted land) and the conventional analysis of Model 1.

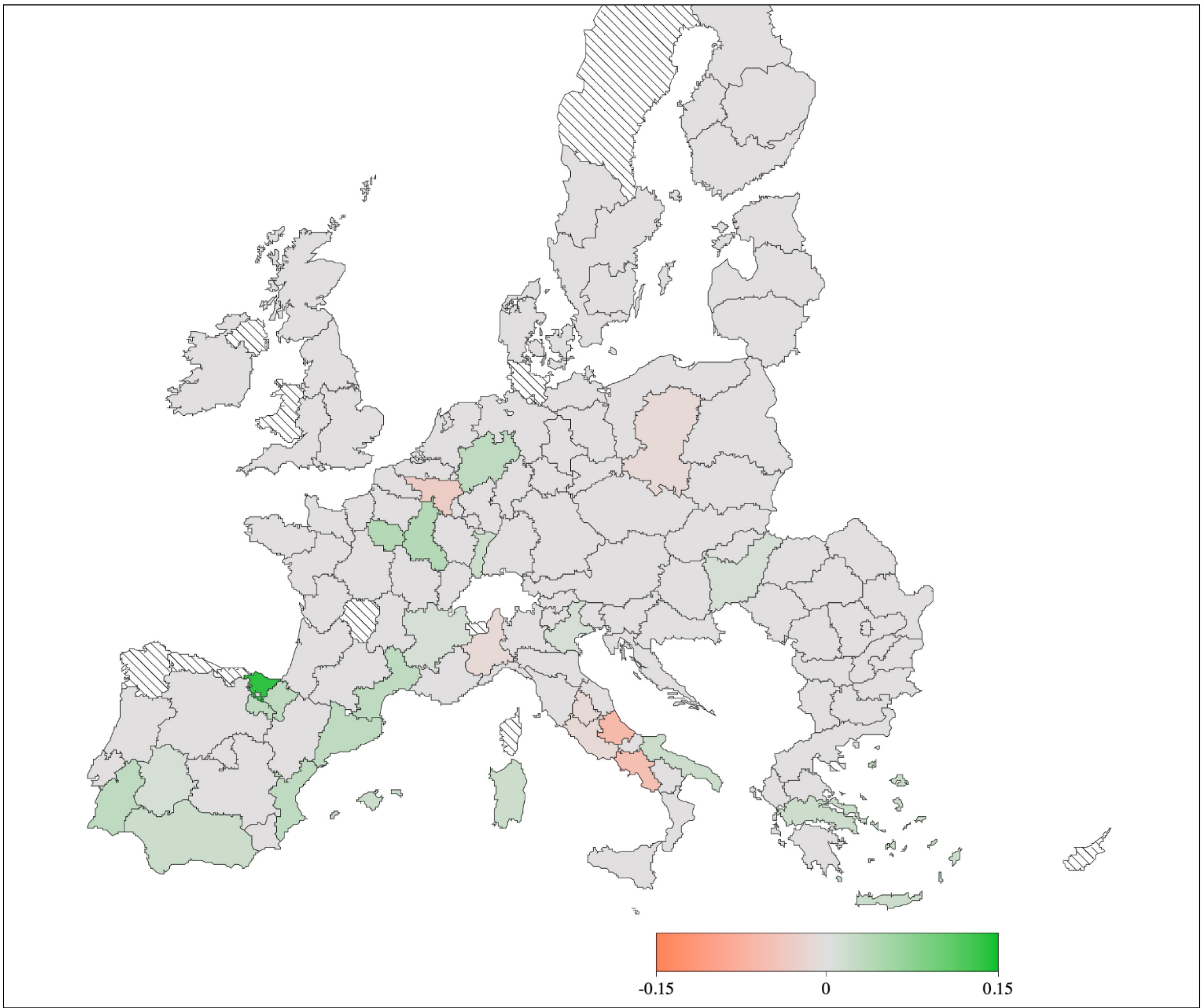
Even though mean efficiency and the majority of regions are barely affected by the recalculation, the plot reveals some interesting differences in the structural pattern of technical efficiency with single in- or decreases of efficiency scores in the range of -0.06 and 0.14.

Most regions performing better than before are located in Mediterranean areas (in particular in Spain, but also in regions of France, Italy and Greece). These regions turn out to be more efficient than they appear in the conventional analysis (Model 1). In contrast, decreasing scores can be found for regions with slightly above average efficiency in Italy, Poland and Belgium. Given the rudimentary adjustment approach we refrain from making detailed remarks about whether those regions could (in principle) be even more efficient than in Model 1 given their good endowment with soil quality. But what our results are able to proof is that not accounting for exogenous factors could seriously deteriorate results and might provoke misleading policy implications. Consider the case of central Italian regions as an example. According to Model 1, the regions of Abruzzo and Campania are found to be substantially more efficient when compared to neighboring regions. Analyses not accounting for environmental factors could conclude that below average efficient neighboring regions should make an effort to adapt or learn from policies or the sectoral structure of Abruzzo and Campania to guarantee for a better input allocation and thus increase their efficiency.

When land quality is taken into account, both regions (and the ordinarily efficient region of Latium) are discriminated due to the inclusion of their com-

5 We checked for robustness by testing the effect on different model configurations, e.g., calculating the model under constant returns to scale and or substituting crop specific costs with crop protection costs as alternative plausible intermediate input. While in some cases, effect and significance of the control variates changed, soil quality remained positive and significant.

Figure 2. Difference between adjusted land technical efficiency scores (Model 2) and technical efficiency scores (Model 1)



Source: own illustration

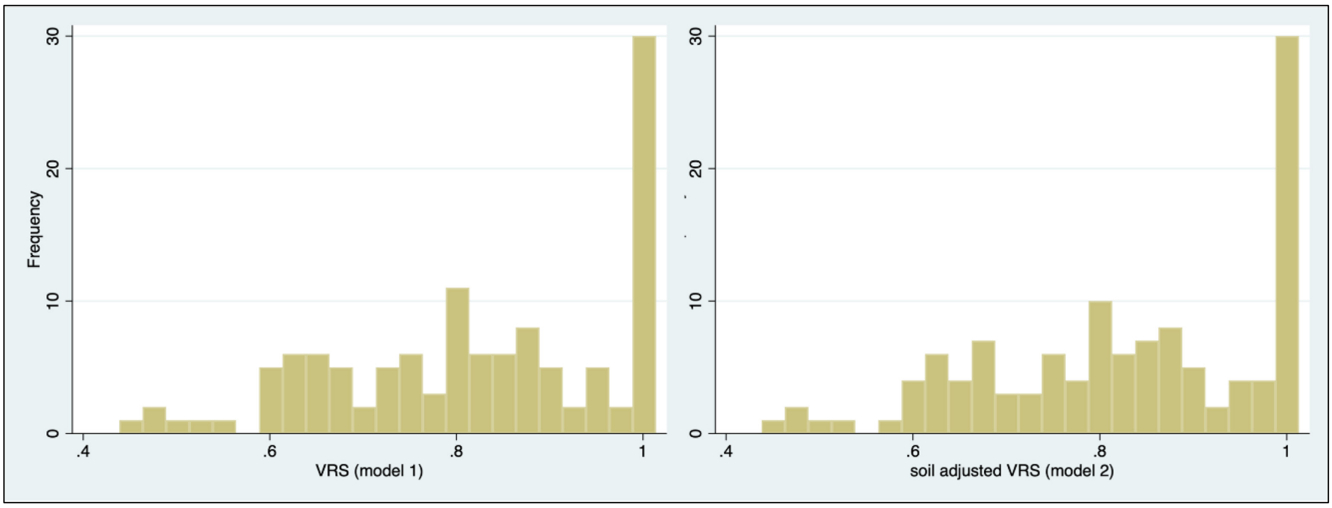
paratively better endowment with land quality. By implementing the adjustment approach, the differences between the regions become more moderate (-6% for Abruzzo and –5% for Campania) and we gained awareness that since land quality does play a role in explaining efficiency variation, it cannot be ruled out that a large part of the differences in efficiency among those regions could be explained by other environmental factors as well. This prohibits the recommendation of policy adaptation of neighboring regions and casts doubts on the general demand for better input use or other managerial policies for improving efficiency, e.g., rationalization or modernization.

The need for considering land quality is further confirmed by the shift in frequencies of efficiency scores depicted in Figure 3.

The left histogram shows frequencies for efficiency estimates of Model 1, the right histogram of Model 2, respectively. A comparison reveals that, even though the patterns seem to coincide on first sight, changes in efficiency estimates are not evenly distributed. Most changes seem to occur for low to average efficiency scores in the range of 0.6 to 0.85. Also, of the 27 regions affected by the inclusion of land quality, 7 regions were 'punished' for good soil quality and 20 regions benefited from the consideration. Given that mean efficiency of the whole sample was barely affected, we would argue that the adjustment approach mitigates extreme effects of exogenous factors rather than punish regions with high land quality.

In both models the number of efficient DMUs amounts to 30 and remains unchanged by the inte-

Figure 3. Frequencies of efficiency scores in Model 1 and Model 2 under variable returns to scale



Source: own calculations

gration of land quality.[6] This explains to some extent why mean efficiency barely changed and presumable changes in efficiency estimates are more likely to be pronounced in models calculated under constant returns to scale and with a smaller input output space. The former is due to the lower probability for such a high share of efficient DMUs of the whole sample, the latter since the adjustment on one of four production inputs will provoke more moderate results than the adjustment of one of two inputs or outputs for that matter.

5 Concluding Remarks and Policy Implications

Comparing agricultural production efficiency and productivity of entities with heterogenous land characteristics makes up a substantial part of the agricultural economics literature. Empirical findings of nonparametric efficiency analysis have continuously emphasized the potential of DMUs to reduce technical inefficiencies by ongoing modernization, rationalization and optimization of their input use (GUESMI and SERRA, 2015, TOMA et al., 2017).

In this paper we have argued that the majority of empirical studies (e.g., employing a two-stage approach) do not sufficiently account for the potential impact of determinate factors on technical (in-)efficiency. Our analysis confirms, for the selected sample of European regions, the findings of previous studies that land quality significantly influences technical efficiency. We extended the commonly employed nonparametric two-stage framework by considering the effect of exogenous environmental factors by adjusting the input land by a land quality factor. A comparison of regular and land quality adjusted efficiency estimates reveals a shift in efficiency pattern that is neither random nor evenly distributed and helps explaining parts of the efficiency variation on the individual level. Since land quality lies outside the regions' sphere of influence, regularly proposed strategies to enhance the seemingly lower efficiency for regions with comparatively poor land quality (e.g., rationalization, intensification) may not have the desired effect because they ignore the naturally imposed limits for productivity growth.

Using the here discussed modified efficiency analysis based on adjusted land could ensure that policy measures are better oriented towards the needs of farmers in regions with comparatively poor land quality, unfavorable agroclimate or geographic conditions. Rather than addressing seemingly lower efficiency (for example by intensifying agriculture and maximizing outputs) policy could support extensive farming practices, on-farm energy production, etc. At the same time, regions with average or higher efficiency might in fact benefit from high soil quality and could (in principle) achieve higher efficiency scores or become efficient.

[6] This too validates the results of the truncated regression analysis. As DARAIO et al. (2018) suggested, results of a two-stage analysis could be invalid when the frontier is affected by the covariates. In our case the integration of the soil quality index by adjusting the input land did not provoke a 'frontier-shift' (all efficient DMUs in Model 1 are also efficient in Model 2), which is why we assume the *separability condition* to hold for our case.

Obviously, the importance of land quality and other environmental factors for crop production is not new but on the research agenda at least since Farrell's pioneering work on efficiency analysis in 1957. Nevertheless, until today, most empirical studies focus on manageable factors. If at all, regions or farms are clustered beforehand, or efficiency scores are decomposed ex post. In contrast, the here proposed process integrates land quality directly into the analysis and maintains the option of conducting an efficiency analysis between DMUs with heterogeneous land characteristics without creating subsets or pooling DMUs according to their land quality (e.g., BHALLA and PRANNOY, 1988; CHAMBERS et al., 2011; GADANAKIS and AREAL, 2020).

Furthermore, the procedure is applicable in nearly all use cases and may be adopted by anyone performing a two-stage DEA framework. Since we identify determinate factors to be mainly geographical and meteorological, data is available for most applications in higher resolution (raster) than necessary to match input and output data.

Also, the approach does not "punish" more extensive farming practices on less fertile land. Furthermore, and perhaps surprisingly, it does not automatically punish regions with very fertile land and highly intensive agriculture either. In fact, most of these regions remain very efficient in both setups. Future research should therefore attempt to construct a pronounced adjustment approach based on deriving the functional relationship of environmental factors and technical efficiency employing the conditional efficiency framework as proposed by BĂDIN et al. (2014) to assess the effect of exogenous factors on agricultural production in detail. This could help to identify pure managerial efficiency in nonparametric agricultural efficiency analyses with a regional, inter-country or international scope and enhance the quality of policy implications, which is essential if saving resources and supplying the globally increasing demand for food shall be realized in the future.

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Appendix

S1. Technical efficiency results of fieldcrops farming in Europe

FADN ID	Name of Region	SYS02 (Tsd.)	UAA	VRS	Soil Adjusted UAA	Soil Adjusted VRS
BEL0341	Vlaanderen	3.38	47.4	1.00	55.7	1.00
BEL0343	Wallonie	3.12	69.2	0.94	89.1	0.91
BGR0831	Severozapaden	3.65	227.8	0.80	201.6	0.80
BGR0832	Severen tsentralen	4.27	157.3	0.83	146.3	0.83
BGR0833	Severoiztochen	3.96	187.0	1.00	192.1	1.00
BGR0834	Yugozapaden	3.69	49.2	1.00	48.1	1.00
BGR0835	Yuzhen tsentralen	4.89	76.7	0.63	69.7	0.63
BGR0836	Yugoiztochen	4.19	159.8	0.73	152.8	0.73
CYP0740	Cyprus	2.61	.	.	.	.
CZE0745	Czech Republic	6.88	191.5	0.81	233.2	0.81
DAN0370	Denmark	12.76	110.9	1.00	126.6	1.00
DEU0015	Schleswig-Holstein / Hamburg	2.17	139.0	0.76	163.9	0.76
DEU0030	Niedersachsen	7.89	100.8	0.89	117.9	0.89
DEU0050	Nordrhein-Westfalen	5.2	69.8	0.95	75.3	0.97
DEU0060	Hessen	3.14	83.9	0.79	90.3	0.79
DEU0070	Rheinland-Pfalz	2.45	97.8	0.85	109.3	0.85
DEU0080	Baden-Württemberg	5.48	66.2	0.82	70.3	0.82
DEU0090	Bayern	12.83	60.1	0.88	65.9	0.88
DEU0100	Saarland	0.15	124.1	0.76	144.4	0.76
DEU0112	Brandenburg	1.08	453.1	0.97	458.0	0.97
DEU0113	Mecklenburg-Vorpommern	1.46	484.2	1.00	497.2	1.00
DEU0114	Sachsen	1.34	245.7	0.94	260.8	0.94
DEU0115	Sachsen-Anhalt	1.84	418.5	0.90	432.3	0.90
DEU0116	Thüringen	0.81	458.4	1.00	499.7	1.00
ELL0450	Makedonia-Thraki	54.48	15.3	1.00	11.3	1.00
ELL0460	Ipiros-Peloponissos-Nissi Ioniou	7.69	10.0	1.00	6.9	1.00
ELL0470	Thessalia	17.39	12.9	1.00	8.3	1.00
ELL0480	Sterea Ellas-Nissi Egaeou-Kriti	15.89	12.0	0.80	8.3	0.82

FADN ID	Name of Region	SYS02 (Tsd.)	UAA	VRS	Soil Adjusted UAA	Soil Adjusted VRS
ESP0515	País Vasco	0.83	66.4	0.74	49.9	0.88
ESP0520	Navarra	4.54	62.9	0.67	50.0	0.70
ESP0525	La Rioja	1.38	45.3	0.73	39.8	0.76
ESP0530	Aragón	15.23	84.4	0.66	57.6	0.66
ESP0535	Cataluña	9.91	35.2	0.65	28.3	0.69
ESP0540	Islas Baleares	0.94	34.8	0.55	25.6	0.57
ESP0545	Castilla y León	36.57	71.5	0.54	56.1	0.54
ESP0550	Madrid	1.56	71.2	0.68	60.1	0.68
ESP0555	Castilla-La Mancha	21.53	85.4	0.68	62.3	0.68
ESP0560	Comunidad Valenciana	3.41	27.2	0.65	20.8	0.68
ESP0565	Murcia	1.28	68.9	0.98	48.1	0.98
ESP0570	Extremadura	8.2	50.6	0.60	35.1	0.61
ESP0575	Andalucía	17.06	53.4	0.79	40.4	0.81
ESP0580	Canarias	0.97	.	.	.	.
EST0755	Estonia	3.35	167.1	0.63	168.7	0.63
FRA0121	Île-de-France	3.43	167.0	0.93	186.4	0.97
FRA0131	Champagne-Ardenne	6.99	151.8	0.89	146.8	0.93
FRA0132	Picardie	6.96	143.4	0.90	179.7	0.91
FRA0133	Haute-Normandie	3.11	143.0	1.00	185.6	1.00
FRA0134	Centre	11.56	145.1	0.94	174.2	0.94
FRA0135	Basse-Normandie	1.52	134.9	0.82	184.6	0.82
FRA0136	Bourgogne	4.02	177.9	0.87	164.8	0.87
FRA0141	Nord-Pas-de-Calais	4.95	83.9	1.00	102.3	1.00
FRA0151	Lorraine	2.53	169.9	0.89	143.2	0.89
FRA0152	Alsace	2.56	61.6	0.94	65.8	0.96
FRA0153	Franche-Comté	0.75	143.8	0.87	127.1	0.87
FRA0162	Pays de la Loire	3.38	95.9	0.90	127.6	0.90
FRA0163	Bretagne	3.75	60.8	1.00	78.8	1.00
FRA0164	Poitou-Charentes	6.92	127.1	0.85	158.4	0.85
FRA0182	Aquitaine	5.21	77.5	0.76	93.8	0.76
FRA0183	Midi-Pyrénées	8.24	96.4	0.65	117.9	0.65
FRA0192	Rhône-Alpes	3.04	82.0	0.91	85.1	0.93
FRA0193	Auvergne	1.34	116.6	0.79	128.6	0.79
FRA0201	Languedoc-Roussillon	1.1	86.4	0.84	79.6	0.88
FRA0203	Provence-Alpes-Côte d'Azur	1.66	67.1	1.00	58.1	1.00
HRV0861	Jadranska Hrvatska	2.71	4.1	1.00	3.9	1.00
HRV0862	Kontinentalna Hrvatska	18.7	33.1	0.60	34.8	0.60
HUN0764	Észak-Magyarország	4.33	81.9	0.63	87.5	0.63
HUN0767	Alföld	34.81	52.2	0.76	42.1	0.78
HUN0768	Dunántúl	17.6	66.5	0.79	65.1	0.79
IRE0380	Ireland	3.74	83.7	0.84	94.9	0.84
ITA0222	Piemonte	13.78	30.4	0.66	32.5	0.65
ITA0230	Lombardia	14.91	32.2	0.67	32.0	0.67
ITA0241	Trentino	0.53	6.4	1.00	5.2	1.00
ITA0242	Alto Adige	0.42	9.6	1.00	8.6	1.00
ITA0243	Veneto	16.3	22.1	0.83	19.3	0.84
ITA0244	Friuli-Venezia Giulia	4.84	21.9	0.81	19.3	0.82
ITA0250	Liguria	0.94	7.0	1.00	7.3	1.00
ITA0260	Emilia-Romagna	21.07	30.4	0.75	30.4	0.75
ITA0270	Toscana	6.75	43.2	0.60	44.6	0.60
ITA0281	Marche	13.12	25.7	0.66	23.6	0.66
ITA0282	Umbria	6.66	29.8	0.63	30.1	0.63
ITA0291	Lazio	11.18	24.9	0.70	24.3	0.69
ITA0292	Abruzzo	5.93	14.7	0.87	14.3	0.81
ITA0301	Molise	4.15	24.5	0.61	27.5	0.61
ITA0302	Campania	14.57	14.6	0.80	15.9	0.75
ITA0303	Calabria	7.31	17.6	1.00	16.5	1.00
ITA0311	Puglia	20.95	25.4	0.63	20.5	0.65
ITA0312	Basilicata	7.2	37.8	0.63	41.3	0.63
ITA0320	Sicilia	16.75	23.7	1.00	18.5	1.00

FADN ID	Name of Region	SYS02 (Tsd.)	UAA	VRS	Soil Adjusted UAA	Soil Adjusted VRS
ITA0330	Sardegna	6.87	32.6	0.61	28.4	0.62
LTU0775	Lithuania	21.56	77.0	0.48	68.5	0.48
LUX0350	Luxembourg	0.08	76.5	0.81	83.1	0.81
LVA0770	Latvia	8.44	94.7	0.51	83.7	0.51
MLT0780	Malta	0.71	.	.	.	.
NED0360	The Netherlands	8.34	58.9	1.00	62.5	1.00
OST0660	Austria	13.62	52.0	0.86	54.7	0.86
POL0785	Pomorze i Mazury	44.83	44.3	0.44	47.6	0.44
POL0790	Wielkopolska and Slask	86.68	27.9	0.48	31.7	0.47
POL0795	Mazowsze i Podlasie	129.9	14.7	1.00	15.8	1.00
POL0800	Malopolska i Pogórze	56.86	13.8	1.00	14.4	1.00
POR0615	Norte e Centro	6.64	10.3	1.00	9.0	1.00
POR0630	Ribatejo e Oeste	3.66	21.0	1.00	18.6	1.00
POR0640	Alentejo e Algarve	3.08	41.9	0.75	32.4	0.78
ROU0840	Nord-Est	11.28	60.7	1.00	62.8	1.00
ROU0841	Sud-Est	18.21	79.3	0.69	79.7	0.69
ROU0842	Sud-Muntenia	20.91	67.0	0.84	67.2	0.84
ROU0843	Sud-Vest-Oltenia	26.1	26.7	0.75	27.4	0.75
ROU0844	Vest	13.62	53.1	0.88	50.3	0.88
ROU0845	Nord-Vest	17.1	29.6	0.74	30.3	0.74
ROU0846	Centru	9.39	38.1	0.87	39.0	0.87
ROU0847	Bucuresti-Ilfov	0.86	53.7	1.00	53.9	1.00
SUO0670	Etelä-Suomi	11.91	67.5	0.80	76.4	0.80
SUO0680	Sisä-Suomi	2.46	47.9	1.00	50.7	1.00
SUO0690	Pohjanmaa	4.37	54.9	0.85	59.6	0.85
SUO0700	Pohjois-Suomi	1.18	74.9	1.00	76.8	1.00
SVE0710	Slättbyggdslän	8.15	119.9	0.73	142.0	0.73
SVE0720	Skogs- och mellanbygdslän	0.75	127.6	0.68	145.0	0.68
SVK0810	Slovakia	2.17	378.6	1.00	386.2	1.00
SVN0820	Slovenia	8.45	9.2	1.00	8.4	1.00
UKI0411	England - North Region	4.96	143.4	0.78	139.4	0.78
UKI0412	England - East Region	12.61	209.7	0.84	236.1	0.84
UKI0413	England - West Region	5.19	144.3	0.80	188.5	0.80
UKI0431	Scotland	3.83	160.4	0.94	190.8	0.94

Source: own calculations