VÍGH Enikő*[1], FERTŐ Imre[2] and FOGARASI József*‡**

Impacts of climate on technical efficiency in the Hungarian arable sector

The aim of this study is to estimate the influence of climate factors on the technical efficiency of Hungarian arable farms. The technical efficiency of farms is affected by several factors such as the technology used, the relative factor abundance, the institutional reforms with the input and output market environment, the farm size and scale economies, the organisation and management, and the farm's specialisation. We employed a two-step approach to identify the impact of climate change on the efficiency of these farms. In the first step, using the Data Envelopment Analysis model, we calculated the efficiency (dependent variable in the second stage of analysis) of these processes. In the second step, we investigated the effect of climate and soil factors (independent variables) on efficiency by applying the Simar and Wilson (2007) approach. In this way we can assess the impacts of matched environmental variables through a robust, representative dataset for Hungary. Our results show that temperature and precipitation increases had statistically significant, positive effects on the technical efficiency of farms in the seeding and vegetative periods in both the constant and variable returns to scale models, and temperature increase during the generative phase of crop production had a negative effect on production efficiency.

Keywords: climate change, arable farms, bootstrap

JEL classifications: Q12, C61, Q51, C31

* Agrárgazdasági Kutató Intézet, Zsil utca 3-5, 1093 Budapest, Hungary. Corresponding author: fogarasi.jozsef@aki.gov.hu; https://orcid.org/0000-0001-7989-8375

** MTA Közgazdaság- és Regionális Tudományi Kutatóközpont, Közgazdaság-tudományi Intézet, Budapest, Hungary.

‡ Also Partiumi Keresztény Egyetem, Oradea, Romania.

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Introduction

The changing climate may cause increasing variability of crop production efficiency and poor economic returns. Between 2006 and 2015, the global average annual surface temperature increased steadily by 0.83-0.89 °C. Globally, 2015 was the warmest year, with a 1 °C increase compared to the pre-industrial period. Meanwhile, European countries experienced even higher (1.5 °C) average temperature rises with respect to the same base period. The summer of 2012 was marked by strong rainfall anomalies, which led to flooding in northern Europe and droughts and wildfires in southern Europe (Dong *et al*., 2013). Trnka *et al.* (2011) estimated that, based on agro-climatic indices in western and central Europe, there is a risk of an increasing number of extremely unfavourable years, which might result in higher interannual yield variability, resulting in poor economic returns. Throughout most of the environmental zones, there were clear signs of agro-climatic condition deterioration and a marked need for adaptive measures. Rainfed agriculture might face more climate-related risks, although the analysed agro-climatic indicators will most likely remain at a level that permits acceptable crop yields.

An extensive body of literature exists on the effects of climate change in the global context on farm-level performance of arable farms. The variations in environmental factors, such as increasing temperature and extreme rainfall patterns, can have a significant effect on agricultural output (IPCC, 2014). Most notably, extreme events such as recently-observed heatwaves and droughts have greatly reduced the yield of some crops (EEA, 2016). More generally, the scientific literature on the impacts of climate change and further environmental externalities reports highly heterogeneous compliance and directions, depending on farm characteristics, regarding the technical efficiency of arable farms (e.g. Olesen *et al*., 2002; Chavas *et al*., 2009; Trnka *et al*., 2011; Trapp, 2015; Hatfield and Prueger, 2015; Vanschoenwinkel *et al*., 2016) The seasonal rainfall and temperature forecasts are expected to have a positive effect on the economic performance of agriculture. However, the effectiveness of climate forecasts on improving technical efficiency is sensitive to the type of climate index used (Solis and Letson, 2012). Temperature is a primary factor affecting the rate of plant development. The warmer temperatures expected with climate change and the potential for more extreme temperature events will have an impact on plant productivity.

In contrast to the above, relatively few studies on the impacts of climate change in agriculture have been conducted in central and eastern European countries. Yet, recent projections (Szépszó and Horányi, 2009; Olesen *et al*., 2010; Mezősi, 2016) identify climate change in the Carpathian Basin as one of the largest uncertainties. This territory, with Hungary at its centre, roughly equates to the so-called Pannonian Biogeographic Region (Sundseth, 2009), which has a temperate climate, with frequent showers and cold, snowy winters and warm summers. The region is characterised by a transitional zone between the humid-continental climate to the north and east, and the humid-subtropical climate to the south and west (Sippel and Otto, 2014). Owing to climate characteristics, the primary impact of climate change is expected to be precipitation change, drought and temperature extremes.

Vanschoenwinkel *et al*. (2016) combined climate, soil, geographic, socio-economic and farm-level data in a linear mixed-effect model and examined whether eastern and western Europe will have the same climate responses, and how these responses will change if regional adaptive capacity increases. They concluded that both regions currently

[1] https://orcid.org/0000-0001-8384-7685
[2] https://orcid.org/0000-0002-3742-5964

have a significantly different climate response, but that if eastern Europe were to implement the same adaptation options as western Europe, it could avoid a large decrease in land value and even benefit from climate change depending on the climate scenario. The research community has responded by monitoring and evaluating climate change effects in both spatial and time scales. Szépszó and Horányi (2009) and Trnka *et al.* (2011) concluded that there is a risk of an increasing number of extremely unfavourable years in both western and central Europe. Accordingly, positive effects on agriculture may become apparent in northern European areas (Olesen and Bindi, 2002). Interannual variability analysis of meteorological variables during the reproductive stage of vegetation result reduced yields but seasonal rainfall and temperature forecasts have a positive effect on economic performance of agriculture (Solis and Letson, 2012).

In addition to the lack of published research in central and eastern Europe, the scientific literature evaluating phenological performance of arable crops from the efficiency perspective is also limited. This paper tries to fill these gaps by (a) investigating the effects of climatic conditions on Hungarian arable farms, and (b) developing the typical phenology phase-based results from an agricultural production efficiency perspective using panel data for the period 2002-2013. We aimed to analyse the extent to which environmental changes may be captured in the efficiency of the cereal, oilseeds and protein crops sector in Hungary, a net agricultural exporting European country. In terms of data, the main feature of our research is the use of high-resolution daily gridded temperature and precipitation data for Hungary, which have not previously been exploited much in climate change and agriculture research.

Methodology

Analytical approach

In the literature, two main approaches compete for efficiency and productivity change calculations: parametric techniques based on stochastic frontier analysis (see Bakucs, 2011), and non-parametric techniques based on Data Envelopment Analysis (DEA) (Coelli *et al*., 1998). We employed a two-step approach for assessing the influence of climatic and soil characteristics on technical efficiency. In the first step, we calculated the technical efficiency of farms using the DEA output-oriented model (Farrell, 1957; Thiele and Brodersen, 1999). The main advantages of DEA are that (a) it does not require any assumption on the functional form, (b) it can treat multiple outputs and inputs, and (c) it is able to determine the best practice for every decision unit (Coelli *et al*., 2005). In this case, we used an output-oriented DEA model for analysis, with fixed input measures. The value of the obtained result is the technical efficiency score for the arable farms. When the efficiency is equal to 1, the farm is considered to be fully technically efficient. However, the standard DEA approach may produce potential bias of efficiency estimates, while the accuracy of DEA results may be affected by sampling variation of the estimated frontier and the non-measurement of random error.

The non-parametric approach focusses on the best operational processes by constructing a production frontier, and all units of analysis are related to this frontier. Thus, the DEA non-parametric technique uses linear programming to construct a deterministic piece-wise efficient frontier using the best-performing observations of the sample. The represented distance from a farm to the constructed frontier represents a measure of efficiency: farms located on the frontier are fully efficient; in contrast, farms under the frontier are inefficient, and the increasing distance from frontier provides less efficient farms (Contreras, 2017).

In the second step of the analysis, we focused on the impact of climate and soil factors on the technical efficiency scores. The DEA estimations provide scores taking values between 0 and 1, and the dependent variables have a censored structure, due to the variables taking values in a limited range (Davidson and MacKinnon, 2003).

Simar and Wilson (1998) first introduced the bootstrap procedure to estimate the uncertainty of traditional statistical inference in DEA. In 2007, they extended their approach to account for the impact of environmental variables on efficiency, in which the factors responsible for the inefficiency may be revealed. Simar and Wilson (2007) algorithms are the only known method for making valid inference in the second stage since conventional methods fail to give valid inference with inappropriate regression results (Keramidou and Mimis, 2011; Benito *et al*., 2014). Simar and Wilson (2007) noted that the DEA efficiency estimates are biased and serially correlated, which invalidates conventional inference in two-stage approaches. They proposed the bootstrap procedure (Simar and Wilson, 1998) that enables consistent inference within models explaining efficiency scores while simultaneously producing standard errors and confidence intervals for these scores. The procedure of Simar and Wilson (2007) completes the instrument for regression analysis of DEA efficiency scores in two-step approaches. Unlike naïve two-step approaches, the Simar and Wilson procedure accounts for DEA efficiency scores being bounded – depending on how efficiency is defined – from above or from below at the value of 1, and for DEA generating a complex and generally unknown correlation pattern among estimated efficiency scores.

Simar and Wilson (2007) went on to (a) define a statistical model where truncated regression yields consistent estimation of model features; (b) demonstrate that conventional, likelihood-based approaches to inference are invalid; and (c) develop a bootstrap approach that yields valid inference in the second stage regression when such regressions are appropriate. They proposed two bootstrap algorithms for solving the two-stage efficiency estimation problem. The algorithm-2 is described in Latruffe *et al*. (2008) and we applied algorithm-1 with 2,000 iterations in our study as follows: (1) a DEA output-orientated efficiency score is calculated for each farm, (2) the maximum likelihood method is used in the truncated regression model, (3) for each farm, bootstrap estimates are performed with 2,000 iterations, and (4) the bootstrap values are able to construct the estimated confidence intervals for each farm.

Data

A representative set of Farm Accountancy Data Network (FADN) data of arable farms were used for DEA calculations for the period 2002-2013 in the first step. The output variable is the gross production value (HUF, deflated) and the input variables are *agricultural land area* (ha), *labour* (annual working unit), *capital* (HUF, deflated), and *intermediate consumption* (HUF, deflated).

We used different soil and meteorological data to check the effects of climate change in the second step. The panel dataset adopted the soil variables *agricul* (dominant limitation to agricultural use of soils), *hwc_sub* (water capacity of subsoil), *hwc_top* (water capacity of topsoil) and *loc* (dummy variable, 1=low organic content below 2 per cent, 0 otherwise) based on the EUSOILS dataset of the ESDA European Union Joint Research Centre (EU-JRC).

In the literature, the EUSOILS dataset is often used as the control variable. Audsley *et al.* (2014) defined available water capacity, saturation to permanent wilting point, soil stoniness and soil texture variables, based on the EUSOILS dataset on soil type-grid combinations, up to 47 different soil types. Moriondo *et al.* (2009) defined the water balance and soil properties (thickness and texture) as variables at grid point scale based on the EUSOILS database, the soil type having the highest frequency within each 50×50 km grid point grid (in every soil mapping unit, SMU) being considered as representative for the whole unit. Fezzi and Bateman (2015) used EUSOILS data as environmental and other control variables. These variables were: soil texture as the share of fine particles (clay), depth to rock and slope. Janssen *et al.* (2008) also used EUSOILS-derived data for integrated environment modelling, where the central concept of the analysis is to define 'representative farms', which defines a 'farm type' in an FADN region in Europe for a specific year. A 'farm type' is specified according to the dimensions of farm size, farm intensity and farm specialisation (by total output: EUR <500 per hectare: low intensity; EUR 500-3000: medium intensity and EUR >3000: high intensity).

In this study, the meteorological variables focused on average daily temperature and daily precipitation variables; based on the AGRI4CAST MARS Crop Yield Forecasting System of the EU-JRC. These variables were divided into three technological sections, the first for the period 1-30 April, the second from 1 May to 30 June and the third from 1 July to 31 August, representing the seeding season for the initial development ($T_{seeding}$, $P_{seeding}$), the vegetative growth stage for stem extension ($T_{vegetative}$, $P_{vegetative}$) and the generative growth stage for the ripening and harvesting ($T_{generative}$, $P_{generative}$) of the crops (Trapp, 2015). These periods are defined for the Carpathian Basin, especially for Hungary, and represent the main crop phases for the relevant crop species (Table 1).

The 10x10 km gridded soil data files were grouped into SMU; each SMU corresponds to a part of the mapped territory and we used the dominant occurrence of SMU for every observed locality. Shares for three soil-related parameters (limitations, organic content and water adsorbtion capacity) and characteristics were constructed for each location.

The temperature and precipitation data were stored in 25x25 km regular latitude-longitude grids. The observed 118 grid points were considered sufficient to allocate the environmental data accurately. The grid-cell information was allocated to location level, which allowed the matching with FADN farm data. In this way we could assess the impacts of matched environmental variables through a robust representative dataset for Hungary.

Results

During the period 2002-2013, the median value of total technical efficiency (constant returns to scale, CRS) of Hungarian arable farms ranged between 0.35 and 0.45 (Figure 1). These low efficiency values indicate a high heterogeneity of farms in production performance, and for poorly-performing farms there is a high potential output increase with this input use.

During the analysed period, around 2 per cent, in the case of the CRS estimation, and about 4-6 per cent, in the case of the variable returns to scale (VRS) estimation, of the arable farms were on the efficient frontier. Pure technical efficiency

Table 1: Descriptive statistics of the variables used in the study.

Variable	Unit	Mean value	Standard deviation	Minimum value	Maximum value
Total output	HUF 1000	39,049.7	97,122.6	90.4	2,034,271.0
Agricultural land	ha	236.7	434.0	1.2	5,506.7
Workforce	AWU	4.0	9.2	0.1	215.7
Capital	HUF 1000	51,671.1	86,240.2	2.7	1,929,056.0
Intermediate consumption	HUF 1000	30,111.1	76,552.9	267.5	1,781,878.0
$T_{seeding}$	°C	12.0	1.1	8.6	16.0
$T_{generative}$	°C	18.5	1.2	14.9	22.3
$T_{vegetative}$	°C	21.9	1.0	18.6	24.6
$P_{seeding}$	mm	37.7	25.9	0.0	135.6
$P_{generative}$	mm	133.0	62.2	7.3	441.6
$P_{vegetative}$	mm	126.8	65.5	18.5	348.2
agricul	% farms	0.97	0.16	0.00	1.00
hwc_sub	% farms	0.55	0.50	0.00	1.00
hwc_top	% farms	0.95	0.21	0.00	1.00
loc	% farms	0.52	0.50	0.00	1.00

Source: own calculations

(VRS) of arable farms accounts for the effectiveness of managerial decisions of farmers, which has been increasing faster than the median value of total technical efficiency (CRS) since 2010.

The results from the double bootstrap estimation based on Simar and Wilson (2007) are presented in Table 2. As mentioned earlier, the dependent variable represents the efficiency of selected arable farms, while independent variables represent the climatic and soil variables. In this context, the temperature and the precipitation increases had a statistically significant positive effect on efficiency of farms in the seeding and vegetative periods in both the CRS and VRS models. In contrast, the temperature increase during the generative phase of crop production had a negative effect on production efficiency: the direction of the effects is consistent with our a priori expectations. Soil dummies were found to have significant coefficients. The biophysical results suggest that the high water holding capacity of the top- and subsoil had a positive effect on efficiency. The same negative relationship was identified for low organic content of soil as we expected: the low organic content of soil lowers the efficiency on both the constant and variable returns to scale models.

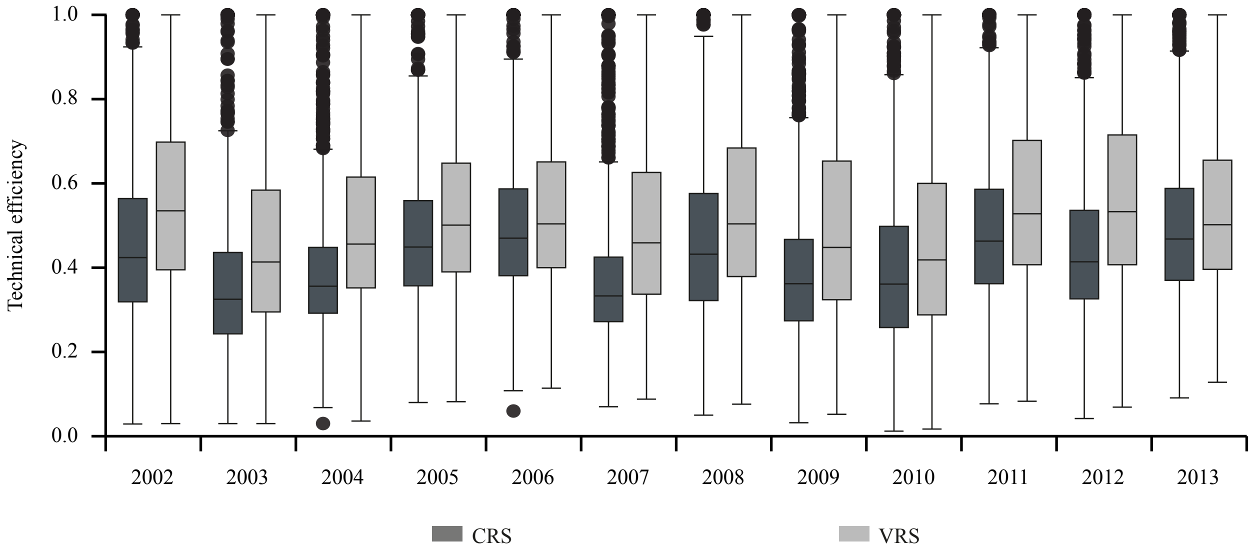

Figure 1: Box plots of Data Envelopment Analysis scores.
Source: own calculations

Table 2: Simar-Wilson regression results.

Explanatory variable	Constant returns to scale	Lower bound	Upper bound	Variable returns to scale	Lower bound	Upper bound
$T_{seeding}$	0.231***	0.1872	0.2741	0.223***	0.1683	0.2771
$T_{seeding2}$	-0.009***	-0.0105	-0.0070	-0.009***	-0.0107	-0.0064
$T_{vegetative}$	0.372***	0.2928	0.4478	0.340***	0.2477	0.4313
$T_{vegetative2}$	-0.010***	-0.0116	-0.0074	-0.009***	-0.0112	-0.0063
$T_{generative}$	-0.225***	-0.3688	-0.0886	-0.309***	-0.4877	-0.1375
$T_{generative2}$	0.005***	0.0014	0.0078	0.007***	0.0028	0.0107
$P_{seeding}$	0.003***	0.0027	0.0036	0.002***	0.0013	0.0024
$P_{seeding2}$	-0.000***	0.0000	0.0000	-0.000***	0.0000	0.0000
$P_{vegetative}$	0.000	-0.0002	0.0003	0.000	-0.0003	0.0003
$P_{vegetative2}$	-0.000**	0.0000	0.0000	-0.000**	0.0000	0.0000
$P_{generative}$	-0.000**	-0.0004	0.0000	-0.000	-0.0003	0.0002
$P_{generative2}$	0.000	0.0000	0.0000	-0.000	0.0000	0.0000
AGRICUL	0.019*	-0.0012	0.0385	0.036***	0.0124	0.0612
HWC_SUB	0.024***	0.0176	0.0311	0.018***	0.0105	0.0262
HWC_TOP	0.014*	-0.0007	0.0299	0.010	-0.0088	0.0278
LOC	-0.013***	-0.0193	-0.0066	-0.017***	-0.0249	-0.0093
cons	-2.001***	-3.3292	-0.6037	-0.701	-2.3527	1.0128
sigma	0.168***	0.1655	0.1704	0.197**	0.1936	0.2000
Wald chi^2	754.831	-	-	388.337	-	-
N	11,785	-	-	11,785	-	-

*p<0.1; **p<0.05; *** p<0.01
Source: own calculations

Discussion

Climate variability is one of the major factors influencing crop productivity, thus farmers' decisions along with their expectations of the coming year's potential outputs are highly affected. The impacts of climate change have been observed on European, including Hungarian, crop and livestock production in recent decades. Variation in the phenology of plants is one of the most sensitive ecological responses to climate change (Menzel *et al*., 2006). In continental climates, temperature increases in the spring can advance the spring phenological phases but warming in autumn and winter may slow the fulfilment of chilling requirements, as evidenced by recent phenology delays in response to warming at some locations. As warming continues, the phenology-delaying impacts of higher autumn/winter temperatures may increase in importance (Guo *et al*., 2014). Our findings illustrate the kind of phenological responses to climate change that can be expected to occur in Hungary. Among the environmental factors affecting agricultural efficiency, our estimations showed that the increasing temperature in the seeding and vegetative periods of plant production (April, May and June) had a positive effect on technical efficiency in Hungarian crop production. By contrast, a negative linkage between temperature and efficiency was demonstrated in the generative period (July and August) when the decreasing water capacity induced lower levels of efficiency. The decreasing precipitation level (e.g. droughts linked to climate change) in the seeding, vegetative and generative periods also had a negative effect on plant production.

Our analysis showed that among the meteorological factors, efficiency in the generative phase is reduced. Similarly, Hatfield and Prueger (2015) concluded that the major impact of warmer temperatures was during the reproductive stage of development and in all cases grain yield in maize was significantly reduced. Our results are also in line with those of Chavas *et al*. (2009), who examined the potential climate change impacts on the productivity of five major crops in eastern China: canola, maize, potato, rice and winter wheat. They found climate variables to be more significant drivers of simulated yield changes than changes in soil properties, except in the case of potato production in the northwest where the effects of wind erosion are more significant. Positive effects on economic performance of agriculture are shown by Solis and Letson (2012), which partly correspond to our results.

Assuming the efficiency scores obtained from the DEA as dependent variables, regression analysis was applied in the second stage of our study to examine the meteorological and environmental variables affecting the efficiency as explanatory variables. From a methodological perspective, the Simar and Wilson (2007) estimation (Table 2) shows that stronger relationships result. The double bootstrap estimation showed that the direction of the effects is consistent with our a priori expectations in the first step.

There is growing concern among policy makers and public interest groups about the effect of climate change on food security and agricultural sustainability. The United Nations Framework Convention on Climate Change aims to combat climate change by limiting average global temperature increases and by coping with the negative impacts. Climatic factors, including temperature and rainfall, have a strong impact on agricultural output, inducing adaptation strategies that can lead to structural changes in farming. In Europe, the Seventh Environment Action Programme of the European Parliament guides the climate and energy framework for handling climate policy goals by conserving natural capital, enhancing resource efficiency and reducing environmental pressures. The outlines of adaptation trends have been developed, and farmers are taking steps to mitigate the negative effects of climate change, such as by changing the timing of cultivations and choosing more appropriate crop species and cultivars. The evaluation of good agricultural practices and factors influencing farmers' decisions is crucial in the agricultural sector.

However, environmental challenges have a strong regional dimension. In the south-east European region, the number of temperature extremes is increasing more rapidly than mean temperature: heatwave intensity, length and frequency have increased. The temperature and precipitation changes also show an increase in return time, although the results are subject to uncertainties (Sippel and Otto, 2014). The Carpathians are subjected to climate change through the weather-related extremes (Spinoni *et al*., 2015). In Hungary, spatial and year-to-year variability of precipitation patterns are notable. The country-wide annual precipitation showed a decreasing tendency during the last century. Owing to the extreme events, there were two floods in the Tisza and in the Danube rivers in 2006 and there was serious inland damage from excess water and other floods (Dong *et al*., 2013). The Hungarian Meteorological Service warns that emerging climate factors, such as increasing number of heat days (for the 1971-2000 period, the average number of heat days was 21) and decreasing number of frosty days (down by 20 per cent from 1900 to 2000) affect both traditional and intensive crop production. Indirect effects of water availability and temperature level show that fertilisers and mineral materials adsorption ability of plants may change considerably.

Owing to different inputs, farmers may apply various adaptation methods according to regional differences through the different climate, technological and soil patterns (Olesen *et al*., 2010). The development of the most appropriate regional- or local-level responses is crucial. Our results showed that the farms, through the climate change effects in the generative phase, achieved lower levels of efficiency in July and August. Our findings can contribute to the necessary development of targeted adaptation strategies to the impacts of climate change for Hungary and its neighbouring countries.

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