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Forecasting Grain Production and Static Capacity of Warehouses Using the Natural Neighbor and Multiquadric Equations

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Abstract

The strategic logistics of agricultural production and storage aggregates information related to production and storage. In this sense, time, location, and distance from producer and consumer markets are considered, emphasizing the importance of grain storage and production logistics. The Natural Neighbor and multiquadric equation are spatial interpolation methods used to predict these variables value at non-sampled locations, for asymmetric and categorical data, respectively. This study investigated the spatial prediction of grain production (tons) (soybean, first crop corn, second-crop corn, and wheat) in the 2016/2017 growing season and qualitative data on the static capacity of warehouses in the 2017/2018 growing season. The result obtained through the spatial interpolation using the natural neighbor method was coherent, as it showed the high variability of grain production relative to the different meso-regions. Therefore, the method was appropriate because it allowed predicting the behavior of grain production in the 2016/2017 growing season in the state of Paraná-Brazil, making it possible to identify regions of higher or lower production. The result of the spatial interpolation using the multiquadric equations allowed identifying a higher predominance of storage units with a low static capacity of warehouses, but also enabled the detection of regions with a static capacity of warehouses that varied from the medium to the high category in the state of Paraná, Brazil.

Keywords

Agricultural, Digital agriculture, Geographic location, Radial basis function, Spatial interpolation.

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Introduction

Brazil stands out as one of the largest food producers in the world, especially in the production of soybean and corn (Cicolin and Oliveira, 2016; Paludo et al., 2020). The state of Paraná is the second-largest Brazilian soybean and corn producer, with a soybean yield of 21.6 million tons (17% of the national yield) and 15 million tons of corn (15% of the national yield) in 2018 (Conab, 2020). Despite the great advances of Brazilian agribusiness in terms of production, the country faces a storage deficit, which limits the efficiency of the system as a whole, increasing the final cost of production (Cima et al., 2020). In the coming years, Brazil will probably have a high storage deficit of its agricultural production (Baroni et al., 2017).

Zdráhal et al. (2021) inform in their in their studies on economic development that Brazil is considered a major exporter of soybean and also has an expressive participation in the production chain of poultry and beef, it also collaborates with the global food supply, within the economic and environmental sustainability vision.

Given the expressive and strategic role that grain production and agricultural storage has in agribusiness in the state of Paraná, the approach the sufficiency of static capacity in warehouses uses indicators of grain supply associated with the demands for storage capacity (Fliehr et al., 2019).

The literature shows that study of geostatistics is a technique that promotes the analysis and prediction of continuous variables that are spread over space and time and that considers the spatial correlation between the sample points at which they are used to map spatial variability (Narany et al., 2014; Bachir et al., 2016; Song et al., 2019).

Accuracy in estimating the spatial distribution of grain production and the static capacity of warehouses requires efficient mechanisms and compatibility of methods and computational resources (Righi and Basso, 2016). Usually, interpolation methods are used to generate distributed surfaces of a given variable from point data. They contribute to the spatial understanding of attributes without the need to collect data in the entire area of interest (Righi and Basso, 2016).

Spatial interpolation methods have been widely used in several areas of knowledge such as Agrarian Sciences with the trend of digital agriculture (agriculture 4.0) and artificial intelligence (Chen and Cai, 2019). The Natural Neighbor interpolation method is expressively used to work with dispersed (asymmetric) data, whereas multiquadric equations are used to interpolate qualitative variables (Tsidaev, 2016; Yamamoto et al., 2018).

Recent studies have shown the wide application and advantages of spatial interpolation methods using the Natural Neighbor (NN) interpolator and multiquadric equations (Belinha et al., 2017; Ku et al., 2020). The spatial interpolation methods NN and the radial basis function, also known as the study of multiquadric equations, allow the knowledge of the spatial behavior of variables at non-sampled locations, facilitating the decision-making (Sampedro et al., 2019; Millan et al., 2020). The multiquadric equations it allows interpolating qualitative variables, which often appears in studies related to precision agriculture (Saeedpanah et al., 2020).

The study of strategies for production and storage contributes to greater prudence and scientific understanding of the challenge that involves the grain production and its relationship the storage system local and regional (Steiner-Neto et al., 2017). Currently, studies have focused on the mapping and interpolation of agricultural data aiming at verifying the spatial variability of soybean yield that is closest to the reality of the planted crop (Dalposso et al., 2019). There is a lack of collective consensus in the literature regarding the choice of the best interpolator, which may be related to extrinsic factors such as the chosen spatial resolution (geographic scale), sample size, and data integrity (Aanjos et al., 2017).

In this sense, the interpolation of spatial data using the NN interpolator is an extremely important computational technique in science and engineering (Sekulić et al., 2020). It is a fundamental tool, being favored by the spatial autocorrelation associated with its covariates (Sekulić et al., 2020).

Sampedro et al. (2019) stated that studies related to the NN interpolation method should pave the way for new studies nowadays. Li, Chen and Luo (2016) and Martyshko, Ladovskiy and Byzov (2016) observed that the NN interpolation method has an effective potential for solving problems in nonlinear data, in addition to being efficient enough to be used in the interpolation of spatial data.

According to Seydaoğlu (2019), the analysis of spatial interpolation using multiquadric equations allows verifications of the variables in studies and higher understanding of this information. Gao et al., (2020), reported that the methods of spatial interpolation through multiquadric equations are widely studied and used in studies, with promising results. In this context, considering the production cycle of soybean, corn, and wheat and the effective demand for static capacity of warehouses, it is necessary to understand the behavior of the spatial variability of these variables, allowing a strategic view of the agents regarding production and storage of the regions.

Yamamoto and Landim (2013) observed the need for a binary coding for regionalized variables with discrete characteristics, and each type that make up the discrete variable is interpolated using multiquadric equations without using indicator kriging due to the need for a variogram for the discrete variable.

Recent studies have shown the effectiveness of the spatial interpolation of discrete variables using multiquadric equations (Zhang et al., 2014; Li and Chen, 2016; Patel and Rastogi, 2017; Yamamoto et al., 2018; Musashi, 2018; Seydaoglu, 2019; Santos and Yamamoto, 2019; Millan et al., 2020). Nourani et al., (2018) emphasized the importance of using the radial basis function, indicating that the efficiency of the method is due to lower uncertainties involved in the obtained data, improved methods that do not use the regular grid, but a radial base function, have become a reference for many studies (Briani et al., 2017; Golbabai and Mohebianfar, 2017; Soleymani and Ullah, 2018; Moradi et al., 2020).

This study aims to show the use of the NN spatial interpolation method in the analysis of grain production, as they are a possible alternative mentioned in the literature.

Another justification of the present study is to show the efficiency of using the interpolation method using multiquadric equations in a qualitative database of the static capacity of warehouses and present its efficiency in the presentation of estimated data at a non-sampled location.

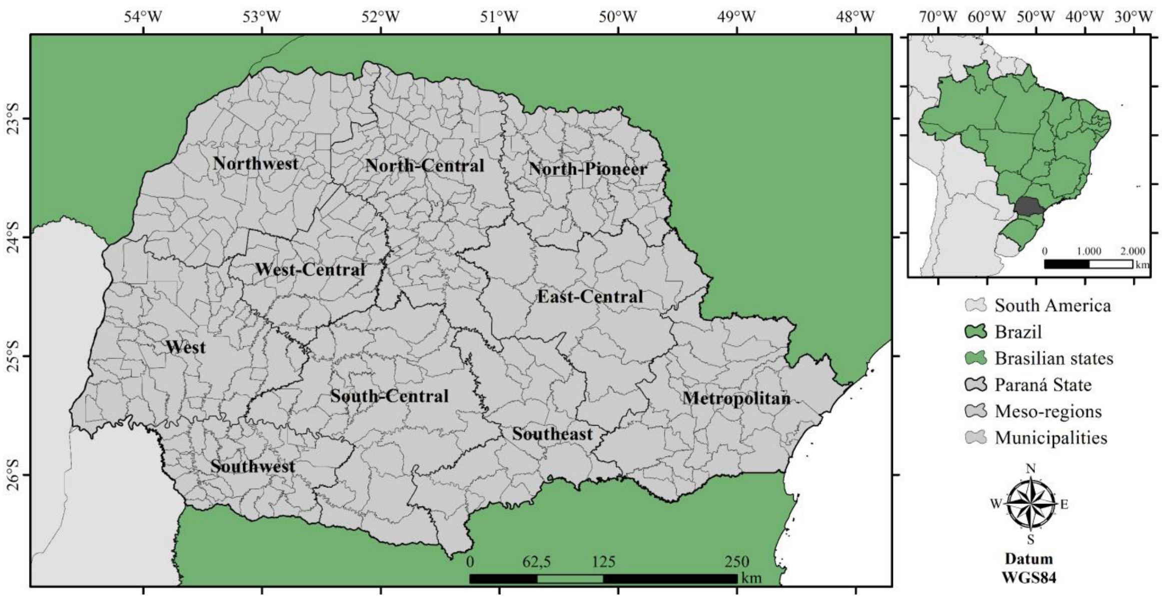
Thus, this study aimed to evaluate the use of the NN interpolation to understand the behavior of the spatial variability of grain production (soybean, first crop corn, and second crop corn, and wheat) in the state of Paraná, Brazil. Also, the present study tried to check the efficiency of the multiquadric equations in a qualitative database of the static capacity of warehouses and present its efficiency in estimate data at a non-sampled location.

The conceptualization and formulation of this study were obtained from the need to understand the spatial behavior of grain production and the static capacity of warehouses in municipalities and meso-regions, as grain production is growing and constant. In contrast, there is an attenuating mismatch and present in grain storage systems in the state of Paraná, Brazil.

Material and methods

The study area comprises the 399 municipalities in the state of Paraná, Brazil, distributed across its ten meso-regions (Figure 1). Georeferenced data on grain production (soybean, first crop corn, second crop corn, and wheat) and static storage capacity in tons were obtained from the National Supply Company (Conab, 2019). This study shows an application of the spatial interpolations Natural Neighbor (NN) from an original database of grain production (tons) in the 2016/2017 growing season (Seab, 2020) and application of the multiquadric equations an database of static capacity of warehouses in the 2017/2018 growing season (Conab, 2019). Exploratory analysis of data on grain production and static capacities of warehouses was performed using descriptive statistics to understand the behavior of these variables under study.

The analysis of the frequency distribution, histogram, and boxplot was performed to verify the behavior of these variables relative to the trend of data concentration (symmetric or asymmetric trend). The variance of the data was also analyzed to verify the dispersion of the data associated with its distance. The coefficient of variation was analyzed according to Cima et al., (2020 b). A coefficient of variation higher than or equal to 30% (CV ≥ 30%) means that the data have high dispersion. For symmetric data exists spatial models, based on geometric criteria in which



Source: Adapted from Seab-Deral (2020)

Figure 1: Delimitation of the study área.

Euclidean distances are considered. Geostatistics in its classic form could not be used, considering the data's asymmetry under analysis (Uribe-Opazo et al., 2012; Tsidaev, 2016). In this study, the variable grain production (tons) is asymmetric.

Sibson (1981) present for asymmetric data, the Natural Neighbor (NN) interpolation method is based on the Voronoi (1908) polygon network of the set of dispersion points. Interpolation using the NN method creates weights for each entry point based on their considered area of influence (Tsidaev, 2016). The interpolation occurs considering the nearest neighbor interpolator (NN), shown in Equation (1).

$$Z(x,y) = \sum_{i=1}^{n} w_i Z_i, \quad (1)$$

on what,

Z is the interpolated value for the regular grid node (x, y), and w_i represents the weights at Z_i of the sample that is next to the subset. For the spatial study of categorical variables the spatial interpolation using multiquadric equations is recommended (Yamamoto and Landin, 2013). This methods have similarity with kriging interpolation used in methodology geostatistics, which uses an omnidirectional variogram for presenting isotropic behavior of the data. Multiquadric equations provide information on non-sampled points as a function of sampled points. In this study, the variable static capacity of warehouses is not numerical but qualitative, being represented by different K=3 levels (low, average and high), which measures the degree of spatial correlation at each specific location. Following is the description of the steps that corresponded to the implementation of multiquadric equations, according to Yamamoto and Landim (2013). The indicator functions are given by Equations (2) to (7).

$$Z^*(X_0) = \sum_{i=1}^{n} C_i \phi(x_i - x_0) + a_0, \quad (2)$$

on what,

C_i, $i = 1, N$: are the coefficients of the multiquadric equation;

a_0: and a constant term that improves the accuracy of the radial basis function (Yamamoto, 2002);

(x_i - x_0): is the distance between the i-th sampling point and the point to be interpolated, following the geostatistical notation, and ϕ is the radial basis function.

According to this information, the multiquadric equation can be used as a local interpolation method, through with neighboring points closest to the point to be interpolated (n). Yamamoto and Landim (2013) demonstrated that Equation (2) can be written in dual form considering all the imposed conditions of restriction, according to Equation (3).

$$Z^*(X_0) = \sum_{i=1}^{n} W_i Z\,(x_i) \quad (3)$$

in which this equation has the constraint condition $\sum_{i=1}^{n} W_i = 1$, that is, a condition equal to that used in ordinary kriging, according to the description below.

The weights of Equation (3) are obtained from solving a system of equations (Yamamoto and Landin, 2013), as shown in Equation (4).

$$\begin{bmatrix} \phi(x_1 - x_1) & \phi(x_1 - x_2) & \dots & \phi(x_1 - x_n) & 1 \\ \phi(x_2 - x_1) & \phi(x_2 - x_2) & \dots & \phi(x_2 - x_n) & 1 \\ \vdots & \vdots & \dots & \vdots & 1 \\ \phi(x_n - x_1) & \phi(x_n - x_2) & \dots & \phi(x_n - x_n) & 1 \\ 1 & 1 & \dots & 1 & 0 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \\ \mu \end{bmatrix} = \begin{bmatrix} \phi(x_0 - x_1) \\ \phi(x_0 - x_2) \\ \vdots \\ \phi(x_0 - x_n) \\ 1 \end{bmatrix}, \quad (4)$$

on what,

μ - is the additional parameter to include the non-bias condition in the multiquadric equation system.

According to Yamamoto and Landim (2013), categorical variables can be measured on a nominal or ordinal scale, and, whatever the scale, there is a discrete number of types. Let k be the number of types of a categorical variable, x_0 is a non-sampled location and n represents values obtained at adjacent points. A weighted linear estimate of this location can be written as per Equation (5).

$$Z^*_{KS}(x_0) = m + \sum_{i=1}^{n} \lambda_i \,[Z(x_i) - m], \quad (5)$$

on what,

m_i: E[Z(x_i)] - represents the means, which are assumed to be known, m_o is the mean at the point x_0, and {λ_i, i = 1, n} represents the weights associated with the n data.

The non-sampled location and sampled points are part of a random function, considering the regionalized variables. The mean and variance of all locations are constant under the condition of second-order stationarity, depending only on Euclidean distances (Yamamoto and Landin, 2013).

According to Yamamoto and Landin (2013), the indicator functions obtained according to the binary coding can be manipulated numerically to interpolate a type at a non-sampled point, according to Equation (6) and Equation (7)

$i^*_{MQ}(x_0; k) = \sum_{i=1}^{n} w_j i(x_j; k),$ (6)

on what the type of the categorical variable interpolated is given by the most likely value of

$i^*_{MQ}(x_0; k)$, where

$i^*_{MQ}(x_0; k_{max}) = \max\,(i^*_{MQ}(x_0\,; k), k = 1, \ldots, K),$ (7)

on what,

K: is the number of levels to be studied.

Spatial weights of the multiquadric equations needed to be corrected due to the presence of negative weights in the kriging and an algorithm was used for their elimination, as proposed by Rao and Joumel (1997). This algorithm was used for such correction. The five closest neighbors were considered, according to the method used (Yamamoto and Landin, 2013).

The software Surfer 12.0 (Golden Software 2014) was used to perform the interpolations of the grain production data in the 2016/2017 growing season using the NN method, while the software R (R Development Core Team, 2020) and Qgis 3.10.1 (Qgis.org. Qgis 3.10 2020) were used for the interpolation of data on the static capacity of warehouses through the multiquadric equations.

The input data for processing were constructed by files in the vector (points) format with the georeferenced location of the grain production points in the 2016/2017 growing season and the static capacity of warehouses in the 2017/2018 growing season (latitude and longitude in UTM). The entire database of the static capacity of warehouses was organized due to the repeated coordinates at various points and the presence of cases of different municipalities with equal coordinates.

The search radius of close values was considered for the analysis of the static capacity of warehouses using multiquadric equations. It was programmed to be variable with a maximum limit of 5 points, according to the methodology of Yamamoto and Landin (2013).

The discretization of data on the static capacity of warehouses required balance. The method used was Jenks natural breaks algorithm method, what identifies the break between classes according to Jenks (1977), being the classification that best represented the spatial distribution of data. The categories of the static capacity of warehouses were named as low (0,91 to 19,575 tons), medium (19,575 to 72,649 tons), and high (72,649 to 265,800 tons) to perform spatial interpolation using multiquadric equations.

The choice of this interpolator was associated with the nature the data, and the discrete variable (count) was transformed into categorical (low, medium and high) and also by the type of map that was desired to be obtained (Yamamoto and Landin, 2013).

Results and discussion

The descriptive statistics in Table 1 shows that the quantitative data of grain production in the 2016/2017 growing season had heteroscedasticities relative to their means, what indicates variability in the grain production, justifying the presence of skewness in the data (Table 1). The same behavior is observed in the static capacity of warehouses, what indicates deficiency the static capacity of warehouses in the municipalities of the state of Paraná, as shown in Table 1.

Figure 2a and Figure 2b show the presence of skewness in the grain production data (t). The data frequency in the histogram (Figure 2a) is located in higher magnitude in the first class. The boxplot (Figure 2b) showed that the data set showed skewness, evidenced by the presence of several discrepant points.

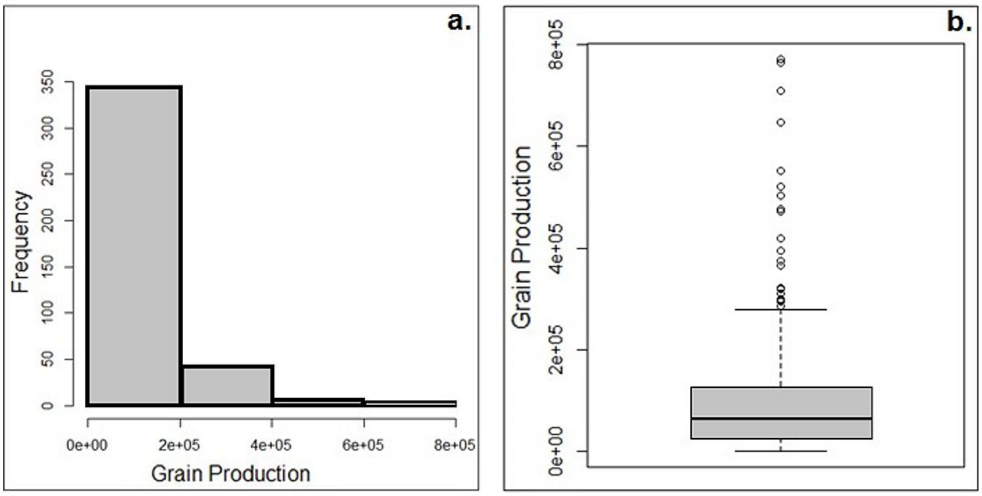
Figure 3 shows the estimated values of grain production in the 2016/2017 growing season using the NN spatial interpolation method. The map (Figure 3) shows regions with higher grain production than other regions.

The data on grain production showed high

Variables	Years	n	Min	$\bar{x}$	Md	Max	Sd	CV(%)	Total
Grain Production	2016/2017	399	0.015	98.620	64.42	772	114	115	39055
Static Storage Capacity	2017/2018	2751	0.091	10.303	4.146	2658	167	162	28332

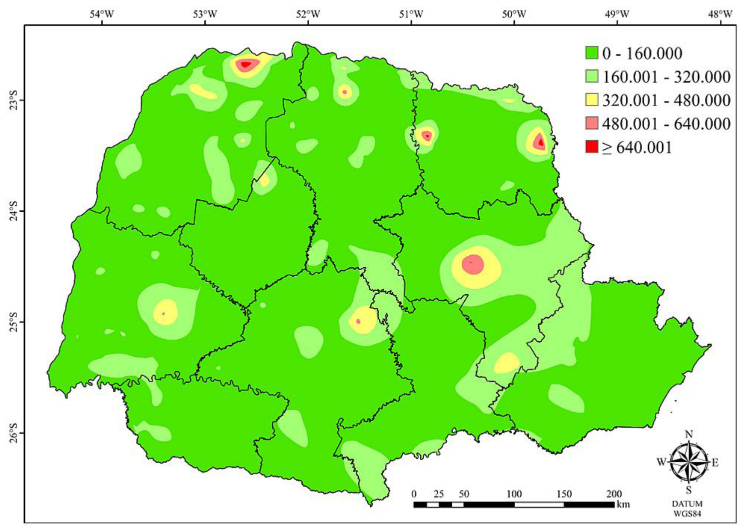
Note: n: number of warehouses for study the static storage capacity and number municipalities for grain production; min: minimum; $\bar{x}$: mean; Md: median; Max: maximum; Sd: standard deviation; CV: coefficient of variation.
Source: own calculations.

Table 1: Descriptive statistics of grain production and static capacity of warehouses, in thousands of tons.



Source: own research

Figure 2: Grain production data. a Histogram. b Boxplot.



Source: own research

Figure 3: Estimated natural neighbor map related to the grain production (tons) in the 2016/2017 growing season by mesoregion of the state of Paraná, Brazil.

variability, considering the different analyzed locations. The meso-regions East-Central, South-Central, West, Northwest, and North presented the largest ranges of values. The ranges varied from 160,000 to 320,000 (light green hue), 320,000 to 480,000 tons (yellow hue) and 480,000 to 640,000 tons (rose and red hue). These results can be justified and represent the practical results obtained in these regions although they are estimated values (Figure 3).

The Northwest meso-region in the state of Paraná, that is, the region of the municipalities of Paranavaí, Querência do Norte, and Terra Rica, showed the highest values of grain production (Figure 3). This agricultural scenario became more evident from 2017 with the opening of an agro-industrial cooperative in this region (Seab, 2020). The meso-regions West and South-Central showed high grain production, which is justified by the large poultry and pig complexes and the presence of agro-industries processing and transforming grains into animal protein.

The meso-regions West, West-Central, and South-Central presented an interesting profile, with an intersection axis showing a high grain storage capacity.

Moreover, the presence of grain production ranging from 0 to 160,000 tons (dark green hue), that is, low grain production, in the ten mesoregions that make up the state of Paraná shows the spatial variability in the grain production. The West-Central mesoregion presented an interesting profile of analysis, as grain production was low in practically all its extension (Figure 3, dark green hue). This region has a low rural population due to the workforce, corroborating with Alves, Andreica and Alcantara (2020), who reported that family farming predominates in the micro-regions of Campo Mourão and Goioerê, with small municipalities and small-scale production characterized by subsistence agriculture. Large industrial hubs are also observed in this meso-region, such as the textile industry. In this sense, Campo Mourão is the municipality that most contributes to soybean and corn the other municipalities have characteristics of small rural properties (Alves et al., 2020).

A similar profile is observed in the meso-regions Southwest, Southeast, and Metropolitan region (Figure 3, dark green hue). According to Seab (2020), the Southwest region is considered a major milk producer and has an expressive presence of textile industries, the Metropolitan region also presented low grain production (Figure 3, dark green hue), as this region has mostly urban characteristics with large clusters of different converting industries, such as the automotive hub (Alves et al., 2020).

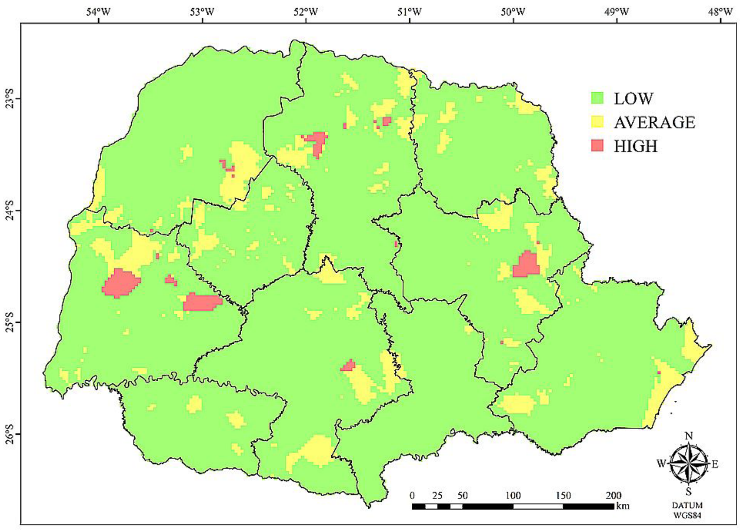
The NN interpolation method presented an efficiency, corroborating with Liu and Chen (2018), who studied the NN interpolation method and identified the viability of this technique, stating that it is a solution procedure reliable and efficient. Karyab, Hajimirmohammad-Ali and Bahojb (2019) reported that the NN interpolation method is appropriate, as it had a lower error rate in the mapping process in spatial data analysis.

Thus, the thematic map of the spatial distribution of grain production in the 2016/2017 growing season (Figure 3) showed that the highest production rates occurred in the meso-regions West, North-Central, East-Central, and South-Central. Additionally, the interpolation through the NN interpolator had a good performance in the spatialization of grain production, considering the 2016/2017 growing season.

The spatial interpolation method using multiquadric equations allowed constructing the estimated thematic map for the static capacity of warehouses for the 2017/2018 growing season, aiming at understanding the behavior and spatial variability of static storage capacities of warehouses (Figure 4).

The categories medium and high of the static capacity of warehouses were more present in the meso-regions North-Central, West-Central, West, and South-Central (Figure 4, yellow and rose hue). This result makes sense since the largest agro-industrial cooperatives and trading companies are located in these regions.

The large cooperatives that leverage the national agribusiness economy are in the West meso-region of the state of Paraná, such as the cooperatives that trade soybean and corn to other countries, as observed by Cima et al. (2020) and Costa et al. (2019).



Source: own research

Figure 4: Map estimated using multiquadric equations related to the static capacity of warehouses in the 2017/2018 growing season by meso-region in the state of Paraná, Brazil.

An average and high storage capacity was observed in the Metropolitan meso-region, as it is a port area responsible for transporting the agricultural production of the state of Paraná through rivers. There was a presence of high static capacity of warehouses were observed in the meso-regions West, (Cascavel), South-Central (Guarapuava and Nova Laranjeira) and East-Central (Ponta Grossa), which is justified by the presence of agroindustrial cooperatives (Conab, 2019). Warehousing units were found only with the category of low static storage capacity in the Southeast meso-region (Figure 4, green hue), characterizing insufficient storage capacity relative to grain production in this region.

The results indicate that the static capacity of warehouses in the low classification was the most abundant category in the state of Paraná, followed by the medium category. The high category was observed less frequently (Figure 4).

The spatialized visualization of the thematic map shows that the high category was more present in the meso-regions Metropolitan, East-Central, North-Central, Northwest, South-Central, and West (Figure 4, rose hue). In this case, the presence of grain storage units with a high static capacity, as observed by Cima et al. (2020).

The estimated map showed sharpness and clarity (Figure 4), allowing a better analysis of the precision in the results found, as observed by Costa et al., (2019). The classification high static capacity of warehouses is observed at low frequency in the state (Figure 4, green hue).

The medium classification, was present more frequently in the meso-regions North-Central, South-Central, West-Central, and West, with storage units with medium total static warehouse capacity.

The demand for warehouses in these regions does not meet the grain supply in its entirety. Similarly, Shah (2015) analyzed the shortcomings in grain storage in India and verificade that the rural sector does not have a structure for grain storage in the country. The most striking scenario is the high frequency of the low classification (Figure 4) for the static capacity of warehouses. This behavior occurs in all ten meso-regions in the state of Paraná. It shows the importance of the interpolation method through multiquadric equations applied in the agricultural data. In this sense, Alatorre et al., (2019) reported the importance of using interpolation using multiquadric equations to analyze the inefficiency of agricultural irrigation in furrows in the Laguna de Bustillos basin, Chihuahua, Mexico, and concluded that the method was efficient.

Figure 4 shows that the interpolation of the spatial location of the static capacities of warehouses varied most frequently from low to medium classification. It shows that the static capacities of warehouses in the state of Paraná are small to medium-sized, thus not following the fast pace of grain production (Seab, 2020).

These results show the importance of the spatial interpolation method through multiquadric equations (Patel and Rastogi, 2017; Amantéa et al., 2018). The temporal and spatial behaviors of the total static capacities of warehouses evidence a predominance of the total static capacity of small warehouses in the state of Paraná, corroborating with the statistics that show the great gap of the accelerated advance of the total grain production relative to the static storage capacities. The deficit of warehouses in the state of Paraná is worrying when compared to the in grain production that has been observed in recent years. Cima et al., (2020) found similar results.

Conclusion

The result showed that the interpolation using the NN method was efficient in analyzing the grain production (tons) in the state of Paraná. The use of the NN interpolator is convenient. It showed that grain production on a larger scale is centered in the meso-regions East-Central, North, Northwest, and part of South-Central and West. Expressive spatial variability was observed in grain production. A similar spatial behavior regarding the static capacity of warehouses was observed in the 399 municipalities of the state of Paraná by means of the interpolation using multiquadric equations. A low static capacity of warehouses was observed in practically the entire state of Paraná, which justifies the insufficiency of storage units relative to the grain production, mainly in the meso-regions West, Southwest, and Northwest, which show a high grain production but a low storage capacity of warehouses. The spatial interpolation of the static capacity of warehouses showed that small storage units for agricultural storage occur more frequently in the state of Paraná. The low, medium and high categories showed spatial variability regarding the static capacity of warehouses, and the high category showed the highest variation.

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Productivity and Efficiency of Precision Farming: The Case of Czech Cereal Production

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Abstract

The paper deals with the sources of competitiveness of Czech cereal production by considering precision farming technology and employing micro-level data collected in the FADN database for the period 2005–2018. The analysis is based on the stochastic frontier modelling of an input distance function in the specification of the four-component model, which currently represents the most advanced approach to technical efficiency analysis. To provide a robust estimate of the model, the paper employs methods which control for the potential endogeneity of netputs in the four-step estimation procedure. Furthermore, the total factor productivity change is calculated using the Törnqvist-Theil index. The results reveal that Czech cereal producers took great advantage of their production possibilities and experienced technological progress, which contributed considerably to productivity dynamics and consequently to an increase in their competitiveness. Precision farming, which is associated with a large number of innovations reflected in technological change and optimal resource use, contributed to higher technical efficiency connected with cost savings in Czech cereal production.

Keywords

Total factor productivity, technical efficiency, precision farming, technology, cereal production.

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Introduction

The rising demand for agricultural products, combined with the need for environmental protection and climate change challenges, has put pressure on agriculture to find innovative farming practices. Precision farming, which is a modern farming management concept using digital techniques to monitor and optimise agricultural production processes (Schrijver et al., 2016), is a way to meet the challenges of sustainable agriculture in the 21st century.

In the last few years, precision farming has been gaining attention in the European Union, although the definition of precision farming can be dated back to the late 1990s. According to the National Research Council (1997), precision farming is like "a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production". However, precision farming is not just about crop production (see e.g. Lovarelli et al., 2020). It is a farming management concept based upon observing, measuring and responding to inter- and intra-field variability in crops or in aspects of animal rearing (Zarco-Tejada et al., 2014). More simply, it is a way to apply the right treatment in the right place at the right time (Gebbers and Adamchuk, 2010). Precision farming utilizes information technology, sensor technologies, satellite technology, Artificial Intelligence (AI), and the Internet of Things for enhancing all functions and services of the agriculture sector (Khanal et al., 2017 and Schrijver et al., 2016). Moreover, precision farming implements techniques and technologies that highlight the relevance of integrating specific ecological principles and biodiversity management procedures into agrospace management, while optimizing inputs to maximize yields (Loures et al., 2020). For example, machine learning technology can be integrated with remote sensing for accurate forecasting of crop production and estimation of nitrogen levels in precision farming (Torky and Hassanein, 2020). This data-driven agriculture can be viewed as one of the main strategies and concepts proposed to increase production efficiency while decreasing its environmental impact (Foley et al., 2011).

Economic as well as environmental studies (Zhang et al., 2002; Zarco-Tejada et al., 2014; Mintert et al., 2016; Schrijver et al., 2016; Balafoutis et al., 2017; Jat et al., 2018; Finger et al., 2019; Soto et al., 2019; Loures et al., 2020) have emphasised multiple benefits from precision farming. Focusing on cereal production, the benefits of precision farming include reducing costs by only applying fertilizers where they are required, based on soil samplings and analysis of the yield data, improving the management of water resources, and optimizing performance through automated harvesting practices (Cisternas et al., 2020). In conventional farming, on the contrary, fertilizers are applied uniformly over fields at certain times during the year. This leads to over-application in some places, with an environmental cost (water pollution), and under-application in others, with an economic cost (reduction of crop yields). Similarly, precision farming uses herbicides and pesticides in specific areas where and when they are needed. Furthermore, controlled traffic methods reducing soil compaction by heavy machinery bring additional economic as well as environmental cost reductions (Zarco-Tejada et al., 2014). The comparative analysis of precision and conventional maize and wheat production presented by Jat et al. (2018) reveals a higher yield of both kinds of cereals and a lower cost in precision farming compared to conventional. That is, precision farming contributes to field efficiency growth (Balafoutis et al., 2017). The yield increase is a result of the compound effect of improved soil health, better water regimes, reduced weed population, and specific nutrient management. The lower cost of production is mainly due to lower costs for tillage, irrigation and weeding (Jat et al., 2018).

The positive effects of precision agriculture are reflected in the efficiency of the conversion of inputs into outputs and in the competitiveness of agricultural producers. Interestingly, in economic research there is a gap in precision farming's technical efficiency and productivity analysis. Moreover, little research has been carried out in the Czech Republic on this topic. The research on technical efficiency and productivity analysis is predominantly devoted to conventional farming. For example, Čechura et al. (2015) analysed the factors determining changes in total factor productivity (TFP) in Czech cereal production based on the Törnqvist-Theil index and the fixed management model. Their results highlighted the role of technological change in productivity growth and recommended targeting agricultural support toward modernization and innovation in the cereals sector. Kostlivý et al. (2020) investigated the technical efficiency of Czech crop-producing farms based on the stochastic frontier true random effect model, taking into account the heterogeneity of farms, and pointed out that innovative crop farms are likely to be more productive. Bokusheva and Čechura (2017) evaluated the TFP and the technical efficiency of crop farms in six member states of the European Union (the Czech Republic, among others) based on the four-error component model introduced by Kumbhakar et al. (2014). Their results confirmed the contribution of technological progress to TFP growth and indicated that sample farms can greatly reduce their costs for producing the same volume of outputs (by 15% in the case of Czech farms evaluated on the sample mean). In crop production, the same four-error component model, which is the most advanced approach to estimating technical efficiency, was also applied by Lien et al. (2018), who analyzed Norwegian crop-producing farms, Addo and Salhofer (2019), who focused on Austrian crop farms, and Pisulewski and Marzec (2019), who investigated Polish crop farms. The efficiency literature deals with Less Favoured Areas (LFA) and organic farming to a lesser extent. For example, Rudinskaya et al. (2019) evaluated the differences in Czech farms' technical efficiency resulting from their location in LFA using a stochastic frontier analysis (SFA) and true random effects model. Madau (2007) applied SFA to estimate technical efficiency in a sample of Italian organic and conventional cereal farms. The results of these studies agree that organic farms and farms situated in LFA tend to overuse resources compared to best-practice farms.

The aim of the paper is to evaluate differences in productivity and efficiency between the group of farmers who use the technology of precision farming and the group of farmers who use standard conventional farming technology. In particular, the study aims to fill the gap in the literature by providing a deep insight into the sources of competitiveness of precision farming by employing new advances in productivity and efficiency analysis and using individual farm data (FADN) with information on precision farming.

The paper is organized as follows: The next section introduces data and a model specification and describes the empirical strategy; then the results and discussion are presented; and the final section summarizes our findings and provides concluding remarks.

Materials and methods

The analysis is based on the currently most advanced approach to investigating technical efficiency, introduced by Kumbhakar et al. (2014) and Colombi et al. (2014). The four-error component model, called the generalized true random effects model (GTRE) by Tsionas and Kumbhakar (2014), allows for the estimation of the persistent and transient parts of technical inefficiency from the same data while considering latent heterogeneity. The distinction between persistent and transient technical inefficiency has significant analytical and political implications because these parts of overall technical inefficiency may vary across farms, for various reasons, and can be corrected by more or less fundamental changes. As Njuki and Bravo-Ureta (2015) have mentioned, persistent technical inefficiency could arise due to the presence of rigidity within an organization and production process. In other words, it reflects structural problems in the organization of the production process or a systematic lack of managerial skills (Filippini and Greene, 2016) and is unchangeable without a new policy or change in the ownership and management of companies (Kumbhakar et al., 2014). Transient inefficiency arises as a result of non-systematic managerial failures that can be resolved in the short term (Filippini and Greene, 2016). It is a result of shocks associated with new production technologies, human capital, and learning-by-doing (Pisulewski and Marzec, 2019).

In this study, the GTRE specification is applied on the input distance function (IDF), which measures the largest factor of proportionality ρ by which the input vector x can be scaled down in order to produce a given output vector y with the technology existing at a particular time t (Caves et al., 1982), formally: $D^I(y,x,t) = \max \{\rho : x/\rho \in L(y)\}$. According to Caves et al. (1982), if $D^I(y,x,t) = 1$, the given output vector y is produced with the minimum amount of inputs at a given time and with the given technology, and a farm is technically efficient.

Implying the homogeneity property of the IDF (Knox Lovell et al., 1994) that is imposed by normalising all the inputs by one input, introducing statistical error term (v_{it}) and latent heterogeneity (μ_i), and replacing $\ln D^I_{it}$ with inefficiency terms: persistent technical inefficiency (η_i) and transient technical inefficiency (u_{it}), that is $\eta_i + u_{it} = \ln D^I_{it}$, the translog IDF takes the form of the GTRE model of M-outputs (y), J-inputs (x), and time (t):

$$
\begin{aligned}
-\ln x_{1it} = {} & \alpha_0 + \textstyle\sum_{m=1}^{M} \alpha_m \ln y_{m,it} + \\
& + \tfrac{1}{2}\textstyle\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mn} \ln y_{m,it} \ln y_{ni,t} + \\
& + \textstyle\sum_{m=1}^{M}\sum_{j=2}^{J} \gamma_{mj} \ln y_{m,it} \ln \tilde{x}_{j,it} + \\
& + \textstyle\sum_{j=2}^{J} \beta_j \ln \tilde{x}_{j,it} + \\
& + \tfrac{1}{2}\textstyle\sum_{j=2}^{J}\sum_{k=2}^{K} \beta_{jk} \ln \tilde{x}_{j,it} \ln \tilde{x}_{k,it} + \\
& + \delta_t t + \tfrac{1}{2}\delta_{tt} t^2 + \textstyle\sum_{m=1}^{M} \delta_{mt} \ln y_{m,it} t + \\
& + \textstyle\sum_{j=2}^{J} \delta_{jt} \ln \tilde{x}_{j,it} t + \mu_i - \eta_i - u_{it} + v_{it}, \quad (1)
\end{aligned}
$$

where subscripts i, with $i = 1,2,\ldots,N$, and t, with $t = 1,\ldots,T$, refer to a certain farm and time (year), respectively. α, β, γ, and δ are vectors of the parameters to be estimated. The symmetry restrictions imply that $\beta_{jk} = \beta_{kj}$ and $\alpha_{mn} = \alpha_{nm}$. The time trend included in the IDF allows for capturing the joint effects of embedded knowledge, technology improvements, learning-by-doing, and input quality improvements (see Čechura et al., 2017). Finally, the error term consists of: $v_{it} \sim N(0,\sigma^2_v)$, $u_{it} \sim N^+(0,\sigma^2_u)$, $\eta_i \sim N^+(0,\sigma^2_\eta)$, and $\mu_i \sim N(0,\sigma^2_\mu)$.

In addition to the estimation of technical efficiency, the specification of the production technology in the translog IDF also allows for calculation of the total factor productivity change using the Törnqvist-Theil index (TTI), defined as the ratio of the revenue-share weighted geometric mean of individual outputs to the cost-share weighted geometric mean of individual inputs (Coelli et al., 2015). Formally, the logarithmic form of TTI is given by (Bokusheva and Čechura, 2017):

$$
\begin{aligned}
\ln\left(\frac{TFP_{it}}{TFP_{i(t-1)}}\right) = {} & \tfrac{1}{2}\textstyle\sum_{m=1}^{M}\left(R_{it,m} + R_{i(t-1),m}\right)\left(\ln y_{it,m} - \ln y_{i(t-1),m}\right) - \\
& - \tfrac{1}{2}\textstyle\sum_{j=1}^{J}\left(S_{it,j} + S_{i(t-1),j}\right)\left(\ln x_{it,j} - \ln x_{i(t-1),j}\right), \quad (2)
\end{aligned}
$$

where $R_m = \frac{p_m y_m}{\sum_{m=1}^{M} p_m y_m}$ are output revenue shares and $S_j = \frac{w_j x_j}{\sum_{j=1}^{J} w_j x_j}$ are input cost shares.

Following Diewert (1976), the TTI can be derived using the parameter estimates of the translog IDF in (1) as the sum of three components: scale effect ($SC = \ln\iota_{it}$), technical efficiency effect ($TE = \ln\upsilon_{it}$), and technological change ($TC = \ln\tau_{it}$) effect:

$$\ln TFP_{it} = \ln\iota_{it} + \ln\upsilon_{it} + \ln\tau_{it}. \quad (3)$$

The scale effect, capturing the contribution of economies of scale, or in other words, of falling average costs as a result of the increasing quantity of output (Mankiw, 2009), is measured as:

$$\ln\iota_{it} = \frac{1}{2}\sum_{m=1}^{M}\left[\left(\zeta_{it,m} + \bar{\zeta}_m\right)\left(\ln y_{it,m} - \overline{\ln x_m}\right) + \right.$$
$$\left. + \bar{\zeta}_m\overline{\ln y_m} - \overline{\zeta_{\iota t,m}\ln y_{\iota t,m}}\right], \quad (4)$$

where $\zeta_{it,m} = (1 - RTS^{-1})\frac{\partial \ln D^I(x_{it}^*, y_{it}, t)}{\partial \ln y_{it,m}}$

and $RTS^{-1} = \sum_{m=1}^{M} - \frac{\partial \ln D^I(x_{it}^*, y_{it}, t)}{\partial \ln y_{it,m}}$.

The technical efficiency effect, associated with movements towards (or away from) the frontier technology, is measured as:

$$\ln\upsilon_{it} = \ln TE_{it} - \overline{\ln TE_{\iota t}}\,, \quad (5)$$

where $TE_{it} = \exp(-\hat{u}_{it})$.

Finally, the technological change component, which captures the improvement in the farm's ability to produce the same amount of output using fewer inputs due to the shift of the transformation function (frontier) over time (Chambers, 1988), is expressed as:

$$\ln\upsilon_{it} = \varphi_{it} - \overline{\varphi_{\iota t}}, \quad (6)$$

where $\varphi_{it} = -\frac{\partial \ln D^I(x_{it}^*, y_{it}, t)}{\partial \ln t}$ (Bokusheva and Čechura, 2017).

The estimation of the GTRE model is undertaken as a multistep procedure. We follow Kumbhakar et al. (2014) and rewrite the model in (1) as:

$$- \ln x_{1it} = \alpha_0^* + \sum_{m=1}^{M}\alpha_{ms}\ln y_{m,it} +$$
$$+ \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N}\alpha_{mn}\ln y_{m,it}\ln y_{ni,t} +$$
$$+ \sum_{m=1}^{M}\sum_{j=2}^{J}\gamma_{mj}\ln y_{m,it}\ln \tilde{x}_{j,it} +$$
$$+ \sum_{j=2}^{J}\beta_{js}\ln \tilde{x}_{j,it} +$$
$$+ \frac{1}{2}\sum_{j=2}^{J}\sum_{k=2}^{K}\beta_{jk}\ln \tilde{x}_{j,it}\ln \tilde{x}_{k,it} +$$
$$+ \delta_{ts}t + \frac{1}{2}\delta_{tt}t^2 + \sum_{m=1}^{M}\delta_{mt}\ln y_{m,it}t +$$
$$+ \sum_{j=2}^{J}\delta_{jt}\ln \tilde{x}_{j,it}t + \alpha_i + \varepsilon_{it}, \quad (7)$$

where $\alpha^*_0 = \alpha_0 - E(\eta_i) - E(u_{it})$, $\alpha_i = \mu_i - (\eta_i - E(\eta_i))$ and $\varepsilon_{it} = v_{it} - (u_{it} - E(u_{it}))$.

This specification ensures that α_i and ε_{it} have zero mean and constant variance. To obtain consistent estimates of technology, as well as productivity and efficiency measures, we use methods which control for the potential endogeneity of netputs, which arises when one or more explanatory variables are correlated with the error term. Following Bokusheva and Čechura (2017), we applied a four-step procedure. In step 1, the two-step system generalized method of moments (GMM) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) is used to obtain consistent estimates of the IDF parameters. The system GMM, which resolves the endogeneity problem and the problem of weak instruments, estimates a model in differences and levels and employs two types of instruments: level instruments for the differenced equations and lagged differences for the equations in levels (Arellano and Bover, 1995). In step 2, residuals are used from the system GMM level equation to estimate a random effects panel model employing the generalized least squares (GLS) estimator. In step 3, the transient technical inefficiency, u_{it}, is estimated using the standard stochastic frontier technique with assumptions: v_{it}~$N(0,\sigma^2_v)$, u_{it}~$N^+(0,\sigma^2_u)$. In step 4, the persistent technical inefficiency, η_i, is estimated using the stochastic frontier model with the following assumptions: μ_i~$N(0,\sigma^2_\mu)$, η_i~$N^+ (0,\sigma^2_\eta)$, and the overall technical efficiency (OTE) is quantified based on Kumbhakar et al. (2014): $OTE_{it} = \exp(-\hat{\eta}_i) * \exp(-\hat{u}_{it})$. All these estimates are done in the SW STATA 14.0.

The analysis uses a panel data set drawn from the Farm Accountancy Data Network (FADN) database and represents the period 2005 till 2018. For the estimation of the IDF in this study, we define the following vectors of outputs and inputs: Cereals output represents the value of the total crops output; other crops output is the difference between the value of total crops output minus cereals output; and other farm output is the difference between the value of farm total output and the value of total crops output. Land is expressed in hectares of farm Utilised Agricultural Area (UAA); capital is represented by capital depreciation and contract work; labour is measured in an Annual Working Unit (AWU, where one AWU represents 1800 working hours per year); and material is defined as total intermediate consumption.

Moreover, we normalize all variables in logarithm by their sample mean. This procedure ensures that we can interpret the first-order parameters as output elasticities and input cost shares, evaluated on the sample mean, respectively. In addition, we rejected farms with less than 3 consecutive years of observations, to comply with the requirements of the system-GMM estimator.

Results and discussion

Table 1 provides a parameters estimate of the input distance function for Czech cereal producers. The results show that the majority of the first-order parameters are statistically significant even at the 1% significance level. Moreover, the estimates meet the theoretical assumptions. Specifically, the results of fitted distance functions evaluated at the sample means are non-increasing in outputs and non-decreasing in inputs. Moreover, the quasi-concavity assumption of the input distance functions with respect to inputs is also met by the estimate. Finally, the AR(2) test and Hansen's J-test statistics indicate the validity of model estimates.

Variable	Coefficient	Std. Err.	p-value
Cereals	-0.516	0.024	0.000
Other crops	-0.274	0.019	0.000
Other farm output	-0.139	0.012	0.000
Land	0.126	0.063	0.046
Labour	0.143	0.040	0.000
Capital	0.158	0.028	0.000
Cereals^2	-0.101	0.034	0.004
Other crops^2	-0.082	0.012	0.000
Other farm output^2	-0.048	0.006	0.000
Cereals*Other crops	0.047	0.016	0.003
Cereals*Other farm output	0.036	0.012	0.003
Other crops*Other farm output	0.009	0.007	0.233
Land^2	-0.232	0.288	0.421
Labour^2	-0.208	0.114	0.071
Capital2	0.107	0.052	0.039
Land*Labour	0.426	0.142	0.003
Land*Capital	0.020	0.094	0.829
Labour*Capital	-0.041	0.073	0.571
Time	0.003	0.003	0.283
Time^2	0.011	0.001	0.000
Cereals*Time	0.002	0.005	0.689
Other crops*Time	0.001	0.004	0.812
Other farm output*Time	0.003	0.002	0.180
Land*Time	-0.014	0.010	0.180
Labour*Time	0.016	0.008	0.060
Capital*Time	0.008	0.005	0.131
Cereals*Land	0.067	0.069	0.332
Other crops*Land	-0.018	0.051	0.725
Other farm output*Land	-0.057	0.033	0.090
Cereals*Labour	0.047	0.050	0.346
Other crops*Labour	-0.069	0.032	0.033
Other farm output*Labour	0.023	0.024	0.353
Cereals*Capital	0.019	0.028	0.496
Other crops*Capital	0.005	0.021	0.811
Other farm output*Capital	-0.014	0.014	0.319
LFA	-0.074	0.025	0.003
Year_2008	-0.250	0.021	0.000
Constant	0.083	0.029	0.004

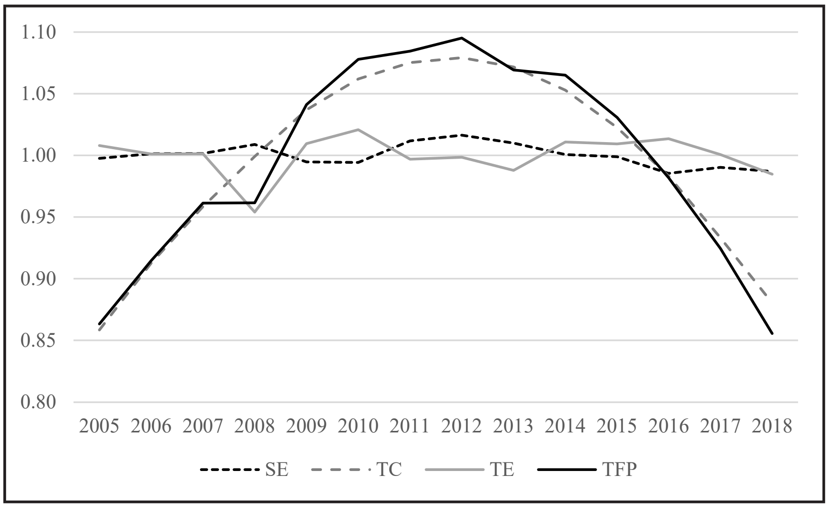
Source: author's calculations

Table 1: Parameter estimate.

First, we evaluate the farm production structure in our data set using the shadow shares of outputs. The results show high cereal specialization in the Czech Republic. The share of cereal output in the total output was 56%, evaluated at the sample means and using the normalisation for the situation with constant returns to scale. The shadow share of other crop output is 29% and the third output accounts for 15%. As far as the cost shares are concerned, we obtained expected results that are consistent with the information we have in our database. In particular, the highest cost share, 57%, was estimated for material inputs. The other inputs (labour, capital and land) have similar shares, between 12% and 16%. As far as economies of scale are concerned, we can conclude that the sample is characterized by an almost optimal size. That is, the average farm operates with almost constant returns to scale.

Technological change is positive and accelerates over time, evaluated on the sample mean. Moreover, we do reject Hicks-neutral technological change. The estimated biased technological change is land-using and labour- and capital-saving. This indicates a successful innovation activity for the sample farms, resulting in cost diminution – an important source of competitive advantage. Moreover, the magnitude of the labour-saving technological change, an example of which is machine-learning technology (for more examples, see Gallardo and Sauer, 2018), indicates the increasing prevalence of precision farming practises in cereal production. Furthermore, it reflects the real wage increase relative to the real rental rate of capital and confirms Hick's induced innovation hypothesis (Irmen, 2013).

The TFP was found to be increasing in the first half of the analysed period, between 2004 and 2012. The average annual growth was 3.4%. However, the opposite is true for the second period, with an average annual decline of 2.4%. That is, the average annual change in TFP over the analysed period is almost equal to zero. Figure 1 illustrates the estimated trends in the distribution of total factor productivity over time, and shows that the main source of TFP change was technological change (TC). Scale effect (SC) and technical efficiency (TE) do not contribute significantly to the TFP dynamics over the analysed period. These results are in line with a study by Bokusheva and Čechura (2017), who found that the TFP growth in French, British, and Czech cereal production was prompted by technological change in the period 2004–2013. This suggests that investments in information, sensor, and AI technologies can accelerate



Source: author's calculations

Figure 1: Total factor productivity and its sources.

productivity and hence increase competitiveness. Consequently, and similarly to Kostlivý et al. (2020), we can conclude that agricultural policies for increasing productivity should concentrate on technological progress.

The initial strong positive technological change in the first half of the analysed period might be related to considerable increases in subsidies that resulted in higher investments. The support for this conclusion can be found in the development of the sample average depreciation. It is well known from the literature that subsidies may influence farm productivity through different channels, which might have a positive or negative impact. Subsidies may negatively impact productivity by causing allocative and technical inefficiency or soft-budget constraints (Kornai, 1986). On the other hand, they may improve the access of farms to innovative technologies and speed up technological change (Bezlepkina et al., 2005). The overall effect is a combination of these channels. Our results suggest that at least in the first period, Czech farmers took advantage of the opportunities of EU accession and improved their productivity by speeding up technological change.

If we concentrate on the comparison between precision and conventional farming, we cannot observe any significant differences, not even in productivity or technical efficiency evaluated on the sample mean. However, as Table 2 illustrates, despite the fact that we do not find significant differences in the mean of technical efficiency and total factor productivity, we can observe that variability is considerably lower in the group of farmers that use precision farming. In other words, if a farmer uses precision farming, then it is characterized by high technical efficiency. Moreover, from a dynamic perspective the farmers who started to use precision farming indicated an increase in technical efficiency. Moreover, they were characterized by higher technological change component as compared to conventional farming, evaluated on the sample mean.

Whole sample	Mean	Std.Dev.	Minimum	Maximum
Overall technical efficiency	0.83	0.04	0.53	0.95
Persistent technical efficiency	0.91	0.03	0.65	0.98
Transient technical efficiency	0.91	0.03	0.63	0.98
Precision farming	**Mean**	**Std.Dev.**	**Minimum**	**Maximum**
Overall technical efficiency	0.82	0.01	0.82	0.83
Persistent technical efficiency	0.91	0.00	0.91	0.91
Transient technical efficiency	0.90	0.01	0.90	0.91

Source: author's calculations

Table 2: Technical efficiency.

The estimated average value of overall technical efficiency (83%), which is similar to the value estimated by Kostlivý et al. (2020), reveals that Czech cereal producers greatly exploit their production possibilities. The overall technical efficiency estimates indicate that, as evaluated at the sample averages, sample farms can reduce their costs by 5% up to 47%. The average overall technical efficiency of precision farming is 82%. The distribution is relatively dense and skewed toward higher values, indicating a cost reduction of 17% to 18%. The persistent and transient technical efficiencies have a similar level, 91% and 90%, respectively, and also a similar distribution.

In other words, systematic and unsystematic managerial failures have a similarly strong impact on the inefficiency of the transformation process in precision farming.

Conclusion

The aim of this paper was to investigate the sources of competitiveness in precision farming, and to evaluate the differences in productivity and technical efficiency between the group of farmers who use the technology of precision farming and the group of farmers who use standard conventional farming technology. Attention was focused on cereal production from 2005 to 2018 using FADN data. From a methodological point of view, the analysis was based on the currently most advanced approach to productivity and technical efficiency analysis. The main contribution of this paper is the empirical application of the recently developed four-error component model to the analysis of the efficiency of precision farming, along with a comparison to the efficiency of standard conventional farming technology, which fills the gap in economic research regarding the analysis of technical efficiency and productivity in precision farming.

The estimated IDF function revealed that Czech cereal production can be characterized by a high degree of specialization, high material intensity, and an almost optimal operational size. In the analysed period, cereal producers exhibited technological progress resulting in cost diminution. The innovation and modernization of production technology was primarily connected with technologies and practices that address specific labour as well as capital constraints.

Technological change was found to be the most important source of the total factor productivity dynamics in the analysed period. Especially between 2004 and 2012, technological progress led to total factor productivity growth of 3% annually. This initial strong positive technological change was probably considerably accelerated by subsidies that resulted in higher investments. That is, the results suggest that at least in the first period, cereal producers in the Czech Republic took advantage of the opportunities of EU accession and improved their productivity by speeding up technological change. Given the speed of technological change and the speed of technological obsolescence, the further focus of agricultural policy on investment support can be recommended, with the aim of increasing the productivity as well as the sustainability of cereal production.

Precision farming is the result of innovative approaches to agricultural production. The new technologies and techniques that it utilizes optimise agricultural production processes, increase yields and reduce economic as well as environmental costs. The optimization of input use is supposed to be converted into a decrease in technical inefficiency. Our study confirmed this statement by uncovering the high density of technical efficiency scores around the mean value in the group of farmers that use precision farming, pointing to the fact that there is a higher loss of resources in the group of companies with conventional technology.

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Assessment of Consumers Acceptance of E-Commerce to Purchase Geographical Indication Based Crop Using Technology Acceptance Model (TAM)

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Abstract

Diffusion of Information and Communication Technology (ICT) in every aspect of life has made the applications of e-commerce a fundamental part of marketing. Hence using e-commerce to market Geographical Indication (GI) based crops is quite essential for the survival of the growers associated with such crops. Due to this significance, it is critical to assess consumers acceptance of e-commerce to purchase geographical indication-based crop. The study uses Technology Acceptance Model (TAM) to validate consumers' willingness of using e-commerce to purchase GI crops with specific reference to Udupi jasmine. To analyse the relationships between TAM variables, Structural Equation Modelling (SEM) technique was adopted. The analysis suggests that behavioural intentions of consumers will influence them into actual e-commerce use. Behavioural intention exerts a significant positive influence on the actual e-commerce use suggests that, if provided with an e-commerce application to purchase the product online, consumers are likely to accept and use it.

Keywords

Technology Acceptance Model (TAM), Structural Equation Modelling (SEM), e-commerce, Geographical Indication (GI), Information and Communication Technology (ICT).

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Introduction

Acceptance of technology is a critical factor for any technology to thrive. In general, acceptance is defined as "the process or fact of being received as adequate, valid, or suitable". Factors that influence user's decision to use a particular system must be considered by decision makers. This would help greatly during the development phase of an application. "Why people accept new technologies?" is a common question of researchers, technocrats, developers etc. and answer to this question may help them to build better methods for designing, evaluating, and predicting the response of the users to the new technologies (Dillon and Morris, 1996). The application of Technology Acceptance Models (TAM) and theories have been used in various domains to understand and predict user's behavior.

Internet technology today has been adopted by many people in their personal and, in their professional life. To gauge people's intention to use e-commerce web application to buy a Geographical Indication (GI) based crop online, one can use certain theoretical models. The theories put forward indicates the factors that will influence the intentions of using technology. The constructs of the model may vary based on the objectives of the research. While analysing people's intention to shop online, Technology Acceptance Model is widely used (Ha and Stoel, 2009; Hassan and Al-Alnsari, 2010). Chuttur (2009) says that while modelling approach in IT research, TAM has captured the most attention of the scientific community. Gefen and Straub (2000) remarks that while predicting information technology adoption TAM is most widely researched models, while Agarwal and Prasad (1997) assert that TAM has been widely accepted among information systems researchers, due to its sumptuous and a great deal of empirical support for it in recent years.

A lot of TAM research has been done

in the aspect of IT acceptance of work-related activity and the theory can also be successfully applied to various non-organizational settings (Argawal and Karahanna, 2000), which also includes e-commerce (Gefen & Straub, 2000; Lederer et al., 2000). The practicality, effectiveness and feasibility of TAM has been shown in several empirical studies. Gefen and Straub (2000) while taking amazon.com as an example analyses a user's behaviour towards the intention to using e-commerce website based on the TAM. While taking MBA students in a commercial college as respondents to carry out the empirical study. They ascertain that PEOU does not affect behavioural intention in a purchasing task but affects behavioural intention in an inquiry task and purchasing something on the website PEOU will affect PU and in turn, PU will affect behavioural intention.

While explaining the consumer's acceptance of shopping online Lin and Lu (2000) asserts that the researcher can use TAM to explain this behaviour. They demonstrate PEOU exerts an indirect influence on behaviour intention through PU and does not have a direct effect on behaviour intention. While studying online shoppers O'Cass and Fenech (2003) validates the application of TAM on retail e-commerce. They determine that PU and PEOU has positive correlation with the attitude of online shopping. It has been proved effective to use TAM to study consumer's attitude towards behaviour intention of using e-commerce and is used widely. Babin and Babin (2001) shows that consumers who feel adept at using online sales or e-commerce systems will have a desire or intention to purchase.

A number of review of literature shows that TAM studies have been applied in e-commerce sites that are selling books (Gefen and Straub, 2000), transactional web sites (Aladwani, 2002), technological fields (Schepers and Wetzels, 2007) etc. From the various related research shown above, while predicting the personal acceptance of use technology TAM has mostly been widely accepted, used and deployed. From the aspect of e-commerce website, TAM constructs usefulness and convenience of use affects the consumer decision to conduct a transaction and are a major factor that affects the use of the website (Syarifudin et al., 2018).

D'souza and Joshi (2019) suggested that an e-commerce framework specific to market GI based crops would prove highly beneficial. Based on this framework an e-commerce web application was built to test willingness of consumers in using e-commerce to buy GI based crop (D'souza and Joshi 2020). Hence to assess consumers acceptance of e-commerce to purchase geographical indication-based crop TAM was used. This would help in understanding the user acceptance of e-commerce web application and further validate the framework proposed by D'souza and Joshi (2019). Structural Equation Modelling (SEM) was employed to analyze the relationships between various TAM constructs.

Materials and methods

It is critical for an e-commerce project to effectively deliver information to the key stake holders. The study uses TAM to validate consumers' willingness of using e-commerce to purchase GI based crops with specific reference to Udupi jasmine. The study uses the e-commerce test web application build using the e-commerce framework proposed by D'souza and Joshi (2020). An essential part of the development of any survey involves the process of framing a questionnaire, determination of the list of questions and designing the format of either written or printed questionnaire (Zikmund, 2003). A questionnaire was designed to cover necessary factors needed for the acceptance of the model among consumers. A pilot study was conducted to this effect and based on the pilot study the questionnaire was refined and modified. While doing so expert opinion was also incorporated for the validation. The questionnaire contained questions on a 5-point Likert scale regarding the different constructs of TAM scales namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioural Intention (BI) and E-commerce Use (EU) and the same are shown in Table 1. Assessment of TAM variables PU, PEOU, BI and EU measured by considering 6 items for PU, 4 items for PE, 3 items for BI and 2 items for EU.

The primary target was the general public who were the consumers of the product. Data was collected through a structured questionnaire by adopting a personal interview technique. Personal interview technique was used as the respondents needed assistance to understand the questions in their local language generally Tulu and Kannada for both Udupi taluk and Mangalore. A total of 122 respondents from Mangalore and Udupi were interviewed based on quota sampling technique, the most important sample in the group of non-probabilistic samplings. By logic, quota sampling is the closest to probabilistic sampling from all non-probabilistic sampling techniques (Yang and Banamah, 2014). The challenge of validation of the developed e-commerce model was met by face-to-face interaction with the selected buyers from both Mangalore and Udupi market. Even though it was a difficult proposition, the fieldwork was done in a justifiable manner with the purpose of understanding the response of the buyers. The sample was chosen among the consumers with the condition that the chosen respondent shall be a buyer of the specific GI product and has familiarity with online shopping.

Test-retest and internal consistency are the two factors employed by this study to ensure reliability (Cooper and Schindler, 2016). Test-retest method was used on a small scale of twenty respondents representing agents and fifteen respondents representing consumers, twice in a period of twenty days. The consistency in the responses given between the two measures are the indicators of a high degree of reliability (Zikmund, 2003). Cronbach's Alpha Coefficient was used as a measure to test reliability. The closer Cronbach's alpha is to 1, the higher the internal consistency reliability (Sekaran and Bougie 2016). For TAM variables the value of 0.75 (for perceived usefulness), 0.73 (for perceived ease of use) and 0.76 (for behavioural intentions) respectively. As determining whether a measure sufficiently covers a content area is not possible through a statistical test, hence content validity usually depends on the judgment of experts in the field (Zikmund, 2003). Hence the validity was determined by experts in the field and changes were incorporated accordingly based on the suggestions. Data collected from the questionnaire administered to the consumers were post-coded and were taken down using a five-point Likert scale with the format of 1 - Strongly disagree, 2 - Disagree, 3 - Neither agree nor disagree, 4 - Agree, 5 - Strongly agree. Coding is done so that the data can be transformed to be suitable for computer-aided analysis (Table 1).

To analyse the relationships between PU, PEOU,

Constructs	Questions	SD	D	A/D	A	SA
Perceived Usefulness (PU)	Buying jasmine online using e-commerce web application would improve my performance (U1).	1	2	3	4	5
	Buying jasmine online using e-commerce web application will improve my productivity (U2).	1	2	3	4	5
	Buying jasmine online using e-commerce web application is useful as it would save me the effort to make my purchases from the market (U3).	1	2	3	4	5
	It is useful to get information on jasmine price on future dates (U4).	1	2	3	4	5
	It is useful to have an option to buy jasmine on future dates (U5).	1	2	3	4	5
	Using e-commerce web application will make it easier to buy jasmine (U6).	1	2	3	4	5
Perceived Ease of Use (PEOU)	Learning to operate this e-commerce application to buy jasmine would be easy for me (E1).	1	2	3	4	5
	It would be easy for me to become skilful at using this e-commerce web application to buy jasmine (E2).	1	2	3	4	5
	Interacting with e-commerce web application to buy jasmine does not require a lot of mental effort. (E3)	1	2	3	4	5
	I feel comfortable purchasing jasmine online (E4).	1	2	3	4	5
Behavioural Intentions (BI)	I am satisfied with the overall process involved in buying jasmine online (B1).	1	2	3	4	5
	Overall, I am satisfied with the features with the proposed online e-commerce web application (B2).	1	2	3	4	5
	Overall, I have a high intention to use e-commerce web application to buy jasmine (B3).	1	2	3	4	5
E-commerce Use (EU)	I would buy jasmine online if an e-commerce web application is provided (EU1).	1	2	3	4	5
	I would like to recommend this e-commerce web application to friends or a family member (EU2).	1	2	3	4	5

Note:Strongly Disagree (SD) - 1, Disagree (D) - 2, Neither Agree nor Disagree (A/D) - 3, Agree (A) - 4, Strongly Agree (SA) - 5
Source: own research and processing

Table 1: TAM variables PU, PEOU, BI and EU measured by considering 6 items for PU, 4 items for PE, 3 items for BI and 2 items for EU (N = 122).

BI and EU in TAM, Structural Equation Modelling (SEM) technique was adopted. While dealing with the latent (unobserved) variables of constructs and their indicators (observed) variables Measurement model comes in handy. It focuses on the link between factors and their measured variables. "SEM technique is preferred for developing complex models. Various types of hypothesized models can be tested using SEM" (Schumacker and Lomax, 2010). For simultaneous estimation of a series of separate multiple regression techniques, SEM is the most efficient estimation technique (Joseph et al., 2010). Measurement model (CFA) and Structural models are components of SEM. The advantage of a structural model is that it allows the researcher to test the predicted relationships between independent and dependent variables. While using SEM the researcher can test the entire theoretical model in one analysis, unlike many other statistical techniques.

As TAM variables are inter-related, SEM is expressed using path analysis with model fit indices. Model fit determines the degree to which the SEM fits the sample data. While considering what constitutes an adequate fit there are no well-established guidelines. But the general approach is to establish that the model is identified, there is a convergence in the iterative estimation procedure, all estimated parameters are well within the range of permissible values, and that the estimated parameters standard errors have reasonable size (Marsh and Grayson, 1995).

There is no single statistical test in SEM that can best describe the strength of the model's prediction. Instead, researchers have developed different types of measures, in combination to assess the results. To asses, the model researchers use numerous goodness-of-fit indicators with reference to model fit. In SEM, ensuring the model fit is the most crucial step. According to Joseph et al., (2010) specific indices are Chi-square Mean/Degree of Freedom (CMIN/DF), Normed Fit Index (NFI), Goodness of Fit (GFI), Root Mean Square Error of Approximation (RMSEA), Adjusted Goodness of Fit (AGFI), and Comparative Fit Index (CFI). The wellness of different indices with different samples sizes, types of data, and ranges of acceptable scores are the major factors to decide whether a good fit exists. Hence based on the values of the fit indices a goodness of fit is established between TAM variables. Analysis of Moment Structures (AMOS) trail version was used to conduct SEM. Statistical significance was set at p-value < 0.005. A p-value of 0.05, a commonly used threshold, means that there is a 5% chance of achieving those results without there being a real effect. A p-value of 0.005 means there is only a 0.5% chance of result without having an actual effect (Johnson, 2013).

Results and discussion

TAM variables were measured by considering 6 items for PU, 4 items for PE, 3 items for BI and 2 items for EU and these items were measured using 5-point Likert scale. The same are presented in Annexure 1. The assessment of TAM variables is shown in Table 2.

Overall, each of the variables were measured by averaging the responses of respondents and assessment was drawn based on the following category:

- If the mean value is less than 2 not at all useful.
- If less than 3 not useful.
- If more than 4 highly useful.

Perceived Usefulness (PU)

Assessment of PU from table shows that respondents strongly agree for item U1 with mean of 4.02 ± 0.9. Similarly, respondents strongly agree for items U4, U5, U6 with mean of 4.46 ± 0.62, 4.57 ± 0.56 and 4.23 ± 0.74 respectively. Whereas they agree for the item U2 and U3 with mean of 3.56 ± 0.89 and 3.97 ± 0.66. Overall PU was found very high among respondents with a mean of 4.13 ± 0.51.

Perceived Ease of Use (PEOU)

Assessment of PEOU from table shows that respondents strongly agree for item E3 and E4 with mean of 4.64 ± 0.61 and 4.49 ± 0.50. whereas they agree for items E1 and E2 with mean of 3.74 ± 0.73 and 3.98 ± 0.72 respectively. Overall PEOU was found very high among respondents with a mean of 4.21 ± 0.50.

Behavioural Intention (BI)

Assessment of BI from table shows that respondents strongly agree for items B1 and B3 with mean of 4.20 ± 0.73 and 4.54 ± 0.62. whereas they agree for item B3 with mean of 3.98 ± 0.72. Overall BI was found very high among respondents with a mean of 4.24 ± 0.50.

E-commerce Use (EU)

Assessment of EI from table shows that respondents strongly agree for items E1 and E2 with mean of 4.49 ± 0.57 and 4.59 ± 0.50. Overall EI was found very high among respondents with a mean of 4.54 ± 0.47.

Structural Equation Modelling using path analysis

Structural Equation Modelling (SEM) was used to assess the goodness of fit between TAM variables and simultaneously analyse the paths in the model. As TAM variables are inter-related, SEM is expressed using path analysis with latent variables. To examine the causal relationships among all constructs, the proposed structural model was tested using SEM. The SEM model fitted between PU, PEOU, BI and EU showed reasonably good model fit according to multiple SEM fit statistics. Results of multiple SEM fit statistics are shown in Table 3. Because there is no single statistical significance test that identifies a correct model given the sample data, it is necessary to take multiple criteria into consideration and to evaluate model fit on the basis of various measures simultaneously.

The structural model for consumer attitude towards e-commerce usage is shown in Figure 1.

The value and analysis of each goodness-of-fit indices is presented as follows:

The value of CMIN/DF = 1.858 where cut-off for good fit must be < 2. Researchers have suggested a value between 1 and 5 is appropriate for chi-square/df. Though a value less than 3 is considered good fit. The value of GFI = 0.874, AGFI = 0.864 where cut-off for good fit must be > 0.85. GFI greater than 0.85 and AGFI greater than 0.8 are acceptable (Joseph et al., 2010). The value of NFI = 0.970 where cut-off for good fit must be > 0.95. For NFI value greater than 0.9 are recommended whereas, values greater than 0.80 are also acceptable (Joseph et al., 2010). The value of CFI = 0.931 where cut-off for good fit must be > 0.90. CFI value should be greater than 0.90. The value of RMSEA = 0.119 where cut-off for good fit must be < 1. RMSEA value below 1 indicates a good fit (Joseph et al., 2010).

As all the values fall within the desired range represent a good fitting model. The path diagram and the table showed that relation between PU and PEOU is significant and positive with $\beta = 0.48$, p=0.001. Further there is significant and positive impact of PU ($\beta = 0.37$, $p = 0.011$) and PEOU ($\beta = 0.56$, $p = 0.000$) on BI. In turn BI has significant positive impact on EU with $\beta = 0.68$, $p = 0.000 < 0.01$. The analysis from SEM suggest that behavioural intentions of consumers will impact in actual E-Commerce use. It is interesting

	1	2	3	4	5	Mean	Std. Deviation
	Row N %	Row N %	Row N %	Row N %	Row N %		
U1	.0%	3.3%	29.5%	29.5%	37.7%	4.02	.90
U2	.0%	9.8%	41.0%	32.8%	16.4%	3.56	.89
U3	.0%	.0%	23.0%	57.4%	19.7%	3.97	.66
U4	.0%	.0%	6.6%	41.0%	52.5%	4.46	.62
U5	.0%	.0%	3.3%	36.1%	60.7%	4.57	.56
U6	.0%	1.6%	13.1%	45.9%	39.3%	4.23	.74
Perceived usefulness						4.13	.51
E1	.0%	3.3%	32.8%	50.8%	13.1%	3.74	.73
E2	.0%	.0%	26.2%	49.2%	24.6%	3.98	.72
E3	.0%	.0%	6.6%	23.0%	70.5%	4.64	.61
E4	.0%	.0%	.0%	50.8%	49.2%	4.49	.50
Perceived Ease of Use						4.21	.50
B1	.0%	.0%	18.0%	44.3%	37.7%	4.20	.73
B2	.0%	.0%	26.2%	49.2%	24.6%	3.98	.72
B3	.0%	.0%	6.6%	32.8%	60.7%	4.54	.62
Behavioural Intentions						4.24	.50
EU1	.0%	.0%	3.3%	44.3%	52.5%	4.49	.57
EU2	.0%	.0%	.0%	41.0%	59.0%	4.59	.50
E-commerce Use						4.54	.47

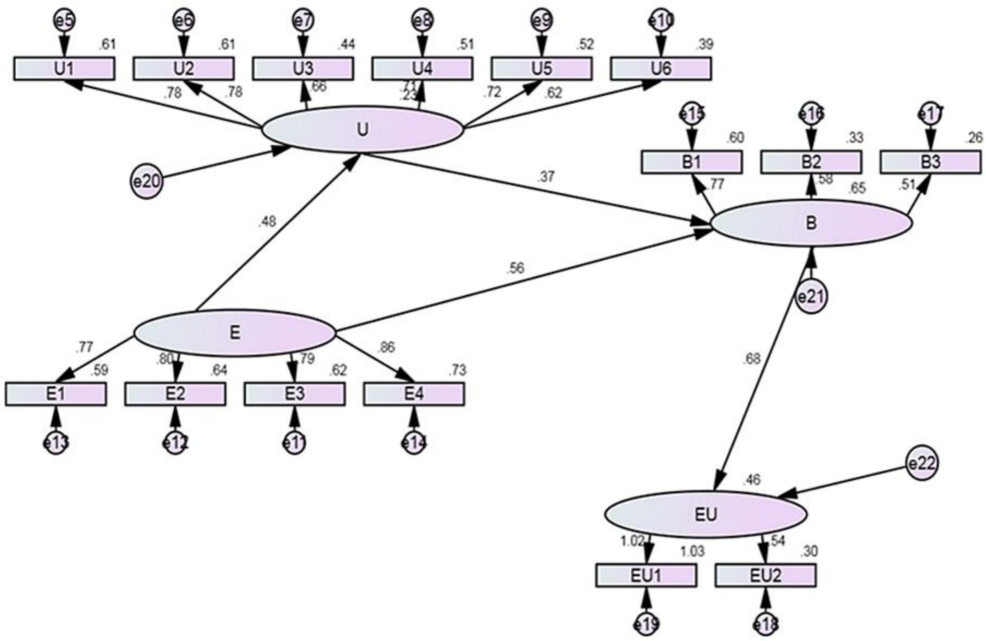
Source: own research and processing

Table 2: Summary of percentage, mean and standard deviations for TAM variables.

	Path		Estimate	p-value	Model Fit Indices
U	<---	E	.483	.001	CMIN/DF = 1.858 GFI = 0.874 AGFI = 0.864 NFI = 0.970 CFI = 0.931 RMSEA = 0.11
B	<---	U	.373	.011	
B	<---	E	.556	.000	
EU	<---	B	.680	.010	
U1	<---	U	.780	.000	
U2	<---	U	.778	.000	
U3	<---	U	.661	.000	
U4	<---	U	.714	.000	
U5	<---	U	.720	.000	
U6	<---	U	.624	.000	
E3	<---	E	.787	.000	
E2	<---	E	.801	.000	
E1	<---	E	.765	.000	
E4	<---	E	.856	.000	
B1	<---	B	.774	.000	
B2	<---	B	.575	.000	
B3	<---	B	.507	.000	
EU2	<---	EU	.543	.000	
EU1	<---	EU	1.0151	.002	

Source: own research and processing

Table 3: Standardized Regression Weights.



Source: own research and processing

Figure 1: The structural model for consumer attitude towards e-commerce usage.

to note that PEOU exerts a greater influence on BI (PEOU -> BI = 0.56) than PU (PU -> BI = 0.37). This suggests that although the consumers find the e-commerce web application to market Udupi jasmine “useful”, the application must be “easy to use”. Behavioural intention exerts a significant positive influence on the actual e-commerce use (BI -> EU = 0.68) suggests that the consumers are willing to use e-commerce in buying the GI based crop if an online web application is provided. Hence it can be inferred that, if provided with an e-commerce application to purchase the GI based crop (Udupi jasmine) online consumers are likely to accept and use it.

Conclusions

Technology Acceptance Model (TAM) has been employed, effectively and suitably, to elucidate and predict the personal acceptance of technology use. Hence successful assessment of consumers acceptance of e-commerce to purchase geographical indication-based crop using TAM shows willingness of consumers in acceptance. Assessment of TAM variables Perceived Usefulness, Perceived Ease Of Use, Behavioural Intention and E-commerce Use was found to be very high suggesting a positive response from the respondents. The SEM model fitted between PU, PEOU, BI and EU showed reasonably good model fit according to multiple SEM fit statistics. As all the values fall within the desired range it represents a good fitting model. The path diagram and the table showed that the relation between PU and PEOU is significant and positive. The analysis suggests that Behavioural Intentions of consumers will influence them into actual E-Commerce use. Behavioural Intention exerts a significant positive influence on the actual E-commerce Use (BI -> EU = 0.68) suggests that, if provided with an e-commerce application to purchase GI based crop online, consumers are likely to accept and use it. Thus, it validates the model (D'souza and Joshi, 2018) using which the web application is built.

As there is willingness among consumers in GI product online the following recommendations are suggested to boost the agricultural e-commerce segment:

- **Promote investment in the agricultural ICT sector.** Through the right policy-framework, improve the business environment that facilitates research, innovation, development along with investment. Public-Private Partnerships are a good example that would encourage investment in ICT infrastructure and applications. Through the right policy-frameworks, development can be accelerated in open source and other technologies that would be easily available to rural small farming communities.
- **Promote linkages between institutions and farming communities through ICT.** An increase in globalization and liberalization of trade have immense benefits and these benefits can be used by agricultural systems. Small farmers need competence in connecting agricultural production with processing of agricultural products, marketing and the creation of grower's organizations. The total system is made up of these small domains of each agricultural disciplines. Linkages between institutions and farming communities through ICT will result in an increase in farmer's competence in agricultural production, marketing, finance and micromanagement of details that would enhance agricultural productivity.
- **Enhance digital inclusion.** The use of a variety of policy measures and technical means to bridge the gap between regions and groups in the country will help to promote access to the internet at a subsidized price for the rural population. Promotion in access to educational content and broadband connectivity in primary education will accelerate digital literacy among the rural population. Targeted technology information among community-based organizations will reduce inequalities in digital literacy levels and promote the development of a workforce for the digital economy.
- **Encourage e-commerce cooperation.** With cross-border trade facilitation, encouraging e-commerce cooperation can strengthen agricultural e-commerce in India. E-commerce cooperation can influence existing and future e-commerce projects to use ideas and concepts that are successful. This will also eliminate the time, effort and resources required to start new e-commerce projects at rural level.
- **Encourage agricultural e-commerce investment**. With the evident profitability of e-commerce in different areas, promote investors to invest in agricultural e-commerce through government support system. This will encourage entrepreneurs to explore different agricultural areas that can take advantage of e-commerce. This subsequently will also attract researchers

to delve into doing research in agricultural e-commerce. This will help the rural community-based organizations to market their produces on a larger scale.

- **Promotion of GI based crops.** With many crops having GI tag in India, government assistance in promoting these crops is quite essential. The government at the state level needs to form special teams to identify the communities that are involved in producing such GI crops and provide assistance to framing communities that are involved in growing these crops. Assistance can be in the form of modern agricultural techniques, use of ICT, marketing, and promotion. This will strengthen these community-based farmers in exploring new techniques that will enhance agricultural production.

Agriculture product promotion is a critical factor for e-agriculture to succeed. Promotion is the element of market mix that includes all the way a firm communicates the merits of its products and persuades its target customers to buy it. Hence, product promotion will assist the product in reaching a larger audience. Presently India has 615 geographical indication (GI) products out of which 103 belong to the agricultural sector. Consumers' willingness of using e-commerce to buy GI based products demonstrates the possibilities of promotion of such agricultural products to a wide range of consumers and organise a largely unorganized sector.

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Time-Varying Integration of Ukrainian Sunflower Oil Market with the EU Market

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Abstract

Ukraine (UA) is one of the world-leading countries in sunflower oil production and sunflower oil exports. Due to the increasing demand caused by biofuel regulations, the European Union (EU) remains the key importer of Ukrainian sunflower oil. Therefore, the aim of the proposed research is to provide an evaluation of the time-varying integration of the UA sunflower oil market with the EU market. To fulfill this goal, first, the trends in sunflower oil production and exports in Ukraine as well as trade regulations are presented. The market integration was assessed using the ARDL-ECM approach that was applied to weekly sunflower oil prices in the period from 2000 to 2020. The analytical study was supplemented with the Toda-Yamamoto (T-Y) Granger causality test, the Bai-Perron multiple structural breakpoint test (B-P) as well as impulse response functions (IRF). This study and the obtained results for the whole sample confirm the presence of a long-run relationship between EU and UA prices. The EU prices are the Granger cause for UA prices, as it is shown in the T-Y test. The Bai-Perron test indicates the existence of multiple structural breaks that can be justified by the market condition and policy modifications. Both the long- and the short-run response of UA prices to changes in EU prices vary significantly in different sub-periods.

Keywords

Sunflower oil prices, spatial market integration, ARDL model, Ukraine, European Union.

JEL code: Q13, Q17, Q28

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Introduction

Spatial market integration

The spatial market integration is defined by the extent, to which domestic markets respond to supply and demand shocks in foreign countries. The absence of market integration has important negative implications for economic welfare. Incomplete price transmission arising due to either economic policies or transaction costs may result in inefficient production and irrational consumption decisions. The signals would not be transmitted between the surplus and deficit regions without market integration, prices would be more volatile, specialization would not take place according to the comparative advantage theory and the potential benefits would not be provided by the trade (Fackler and Goodwin, 2001).

The fundamental analysis of spatial market integration is founded on a spatial equilibrium model and the concept of spatial arbitrage (Barrett and Li, 2002). If price differences are lower than the trade cost, there is no propensity to trade and shocks are not transmitted between regions. However, if price differences exceed the trade cost, this encourages arbitrageurs to act and transfer goods from the surplus to deficit markets, which is manifested in the co-movement of prices. A perfectly integrated market that passes price information quickly and fully is commonly assumed to be efficient (Bakucs et al., 2019). According to research publications, the transmission of shocks between different regions is frequently related to the Law of One Price (LOP) (Svanidze and Götz, 2019). The LOP states that homogeneous goods in spatially separated markets (locations) will have the same price when expressed in the same currency and adjusted by trade costs. The LOP concept is often assumed to be appropriate in the long-run; however, most of the studies indicate deviations from the LOP in the short-run.

However, if trade costs are fluctuating, the propensity to trade also varies and, as a result market integration is not constant over time. Therefore, the long-run equilibrium relationship and short-run price adjustments might be also time-varying. Results of empirical research for agricultural commodities indicate such a possibility (see e.g. Götz et al., 2016). Factors affecting the trade cost and thus agricultural market integration include market infrastructure, foreign and domestic policies, inter-regional imbalances, imperfect competition, product homogeneity or exchange rates (Conforti, 2004; Marwa et al., 2017; Braha et. al., 2019). They alter the market equilibrium by weakening the flows of products between international and domestic markets. Policy instruments are key factors, in turn influencing trade costs. However, it is worth emphasizing that tariffs, tariff-rate quotas, or export and import quotas and bans differently influence market integration and price transmission processes (Rapsomanikis et al., 2006; Listorti and Esposti 2012).

Ukrainian sunflower market

The global economic growth as well as an increasing role of renewable energy policies have produced new challenges for agriculture over the last decades. The Ukrainian oilseed sector has benefited from these changes. In the last twenty years, the domestic production of sunflower oil has increased over 7-fold, while its export grew 11.5-fold. According to the sunflower oil balance sheet, in the 2019/2020 marketing year (MY) the UA industry produced 7 million tons of sunflower oil, of which 90% were exported (Table 1).

Ukraine is a major producer and exporter of sunflower oil in the world. In 2019/2020 MY Ukraine had a 30% share in the world production and a 51% share in the global sunflower oil trade. In 2000/2001 MY the above-mentioned shares were 13 and 25%, respectively. India, the EU, China and Iraq are the top buyers of Ukrainian sunflower oil. In 2019/2020 MY they collectively purchased over 86% of Ukraine’s annual exports (USDA-FAS, 2020).

The key aspects affecting the growth of Ukrainian sunflower oil production and export are domestic and international policies. Ukraine, similarly to most oilseed producing countries worldwide, applies the Differential Export Tax (DET) to promote the export of oil instead of seeds. On the other hand, importing countries as a response to DETs apply import tariffs on vegetable oil, but no tariffs on oilseeds (Bouët et al., 2012). In Ukraine the DETs consist of a single export duty on sunflower seeds, whereas exports of oils and meals are not taxed. The export tax on sunflower seeds (23%) was introduced in 1999; however, it was reduced to 17% in 2001 and to 16% in 2005. After accession to the World Trade Organization (WTO) in 2008 the export tax rates were gradually decreased to 10% in 2013 (Shmygol et al., 2013; Tulush and Hryshchenko, 2018). As a result of such a policy, almost all grown sunflower seeds are domestically consumed or processed for sunflower oil.

The biofuel policy has also contributed to the increase of Ukrainian production and export of vegetable oils. Proposed requirements and biofuel regulations introduced by developed countries have significantly influenced agricultural markets worldwide, even in the countries which did not support such initiatives (Zilberman et al. 2013; Hamulczuk et al., 2019). The EU biofuel policy was crucial for the development of the oilseed markets

Marketing year	2000/2001	2005/2006	2010/2011	2015/2016	2019/2020
Beginning Stocks	12	293	144	344	40
Production	970	1925	3335	5010	7055
Imports	0	0	1	1	0
Total Supply	982	2218	3480	5355	7095
Exports	550	1514	2652	4500	6350
Domestic Consumption	417	417	530	550	545
Total Demand	967	1931	3182	5050	6895
Ending Stocks	15	287	298	305	200
Self-sufficiency ratio	2.33	4.62	6.29	9.11	12.94

Source: the authors’ calculations based on USDA-FAS (2020)

Table 1: Sunflower oil balance sheet for Ukraine, thousand MT.

in Ukraine (Kretschmer et al. 2012). As a result of the increased demand for sunflower oil, the EU has become the main export destination for Ukrainian sunflower oil. The volume of sunflower oil exports from Ukraine to the EU has increased around 13-fold in the last 20 years (USDA-FAS, 2020). This tendency confirms the increase in the integration of these markets, measured by the flow of goods.

The purpose of the study

Nowadays, globalization and international integration processes in agriculture and food commodity markets may lead to the trade creation and trade diversion effects. The fluctuation of trade barriers resulting from changes in customs rates, non-tariff restrictions and transportation costs, as well as multilateral or bilateral agreements will potentially result in the time-varying linkage of international agricultural and food markets. In this context, questions related to the nature of price linkages between agri-food markets in various countries or regions and the strength of these links remain problems of current importance. The literature on the spatial integration of Ukrainian agricultural commodity markets is limited in scope mostly to grain markets (e.g., Goychuk and Meyers 2014; Potori and Józsa, 2014; Götz et al., 2016) or the rapeseed market (Hamulczuk et al., 2019). Some of these sources refer to the potential time-varying linkage between the markets. Despite the importance of sunflower seed and sunflower oil markets in Ukraine, few papers published by Ukrainian researchers are related to the economic aspects of these markets. Instead, most of them focus on general policy, market efficiency and international marketing issues (e.g., Shpychak et al., 2015; Barsuk, 2017; Tulush and Hryshchenko, 2018). To our best knowledge, the only paper related to the investigation of price linkages between Ukrainian and international sunflower markets is by Kuts and Makarchuk (2020). However, the research presented there is based on monthly data and does not refer to the possible changes in the strength of price transmission over time.

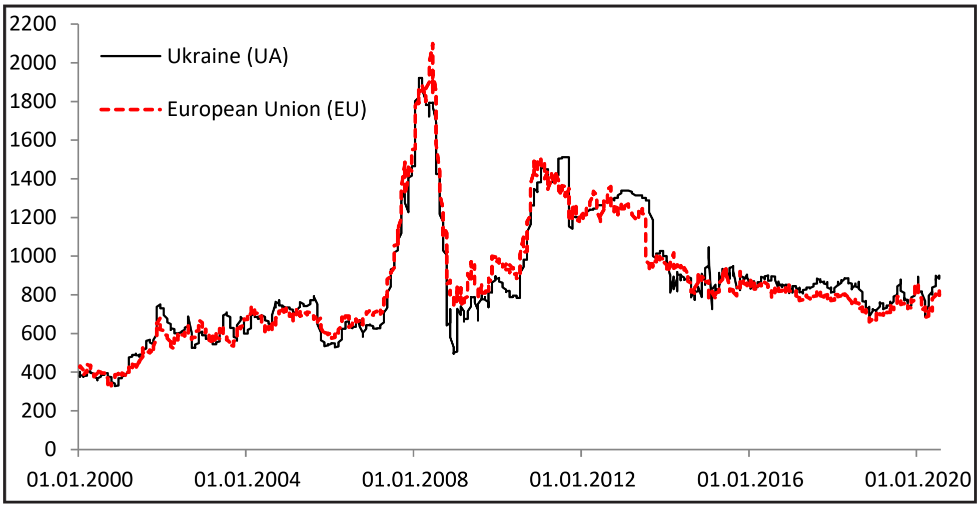
Taking into account all the issues indicated above, the aim of this paper is to evaluate the nature of the time-varying integration of the UA sunflower oil market with the EU market. In this study the price linkage between sunflower seeds was not analyzed, because it is sunflower oil, not the seeds, that is the subject of bulk international trade. In our opinion, this is the first study being an attempt to assess the spatial integration of UA with foreign sunflower oil markets based on the price transmission approach. To fulfill this goal the Granger causality test, the ARDL-ECM model and multiple structural breakpoint tests of Bai-Perron were applied based on weekly price data in 2000-2020. To facilitate the interpretation of price adjustments the accumulated Impulse Response Functions (IRF) were estimated. To provide specific insight, the rest of the paper is structured as follows: section 2 presents data and methods of empirical investigation, section 3 reports on the results and provides their discussion and the conclusions are presented at the end of this paper.

Materials and methods

Spatial market integration can be measured using different approaches and data (see e.g., Barrett and Li, 2002; Listorti and Esposti, 2012). Nevertheless, two concepts dominate in the literature on the subject. In one approach the integration is referred to as the process of interlinkages between market participants, which are reflected by the trade flows. The other concept refers to the co-movement of prices in various locations resulting in both the trade and information flows. The price approach was used in this study to assess the nature of UA and EU sunflower oil market integration. The coverage period of the weekly sunflower oil price series extends from January 2000 until July 2020 (Figure 1). Ukrainian sunflower oil prices are ex-works, whereas the UE data are FOB prices in Rotterdam, being the representative market for the EU.

The first step in the preliminary analysis includes testing the order of integration for price series with the use of the Augmented Dickey-Fuller (ADF) test. In order to determine the endogeneity of the variables, the Toda-Yamamoto (T-Y) causality test based on the ARDL approach is performed. This test is based on the pair of equations similar to Equation 1, but without the contemporaneous lag (see for details Toda and Yamamoto, 1995).

After the preliminary analysis had been performed, it was decided to use the ARDL-ECM approach (Pesaran et al., 2001). The applied method has some advantages over the conventional co-integration analysis, because it can be used regardless of the fact whether the underlying series are I(0), I(1), or even fractionally integrated. The only restriction is that the analyzed series cannot be I(2) integrated. This model can also include contemporaneous price reactions. The general version of the ARDL (p, q) model for two price



Source: the authors' study based on APK-Inform

Figure 1: Weekly sunflower oil price series used in the study (USD/metric ton).

series (Y_t and X_t) may be presented as follows:

$$Y_t = \mu_0 + \mu_1 t + \sum_{i=1}^{p} \alpha_i \, Y_{t-1} + \sum_{i=0}^{q} \beta_i \, X_{t-i} + \varepsilon_t \quad (1)$$

where: Y_t, X_t are dependent and independent variables, respectively (in our case Y_t is Ukrainian sunflower oil price and X_t is EU sunflower oil price, the booth in logs), μ_0 and $\mu_1 t$ reflect the deterministic part of the model (constant and linear trends), α_i and β_i are other parameters, ε_t denotes white noise errors. The number of lags (p, q) can be adopted based on information criteria assuring no autocorrelation in residuals (LM test). The model can be estimated OLS or other robust methods (e.g., HAC). The above model may be transformed into an unrestricted (conditional) ARDL-ECM form that may be used for co-integration testing:

$$\Delta Y_t = \mu_0 + \mu_1 t + \sum_{i=1}^{p-1} \alpha_i \, \Delta Y_{t-i} + \sum_{i=0}^{q-1} \beta_i \, \Delta X_{t-i} +$$
$$+ \pi_1 Y_{t-1} + \pi_2 \, \Delta X_{t-1} + \varepsilon_t \quad (2)$$

where: α_i and β_i represent short-run dynamics, π_1 and π_2 allow us to estimate the long-run relationship.

The existence of the long-run relationship between the variables was tested based on F-test statistics. The null hypothesis of no co-integration (H0: $\pi_1 = \pi_2 = 0$) is tested against an alternative hypothesis assuming the presence of co-integration between the variables (H1: $\pi_1 \neq \pi_2 \neq 0$). Calculated F-test statistic values are compared with two sets of critical values, after Pesaran et al. (2001). If the F-statistic is below the lower bound critical value, then the null hypothesis of no co-integration cannot be rejected. When the F-test statistics exceeds the upper critical value, then the null hypothesis of no co-integration can be rejected. If the computed F-statistic falls between the lower and upper bounds, then the results are inconclusive.

Taking into account possible time-varying price transmission, the stability of parameters was tested by the CUSUM standard and CUSUMSQ tests (Brown et al., 1975). Moreover, to test the parameter stability and structural change in the ARDL-ECM models different versions of the Bai-Perron multiple breaks test were applied (Bai and Perron, 1998). These tests were conducted on the L+1 vs. L sequentially determined breaks, L+1 vs. L globally determined breaks and 1 to M globally determined breaks. After assuming the structural breaks new ARDL-ECM models for each subsample were estimated. The whole analysis was summarized by computing dynamic multipliers (IRF), which show the amount of information each exogenous variable contributes to the endogenous one. The empirical analysis was performed and presented in two dimensions: a) for the whole sample (assuming no time-varying price transmission, which can be the starting point for the next step), and b) assuming and testing time-varying price transmission.

Results and discussion

The whole sample analysis

The empirical analysis was started with the unit root test (ADF) for the logarithmic price series as well as their first differences (d). In the entire study sample, it can be concluded that no series is integrated of order two I(2). The ADF test indicates that logs of the UA series are stationary (the null hypothesis assuming non-stationarity is rejected at 5% significance levels (t-stat = 2.93, p = 0.043), whereas logs of the EU price series are integrated of order 1 (Table 2). The results of the ADF test for price series justified the use of the ARDL-ECM framework, which is robust for the non-stationarity assumption in testing long-run relationships.

ADF test		
Variable	No. of lags	t-stat
UA	14	-2.927**
d_UA	13	-7.258***
EU	6	-2.581*
d_EU	5	-10.897***
Toda-Yamamoto causality test		
Independent variable	No. of lags	F-stat
EU	9 (AIC)	10.662***
UA	9 (AIC)	1.769*

Source: the authors' study

Table 2: Results of unit root and Granger causality tests (based on log data).

It was expected that UA prices are endogenous to prices in the EU. To verify this hypothesis the Toda-Yamamoto test based on the ARDL model was applied (Equation 1), but without taking into consideration the contemporaneous lag and assuming $p = q$ (see details in Toda and Yamamoto, 1995). Due to the heteroscedasticity, the testing model was estimated with the HAC standard errors. Optimal lags were established using the Akaike information criterion (AIC) based on the VAR model ($p = q = 9$) and increased by one due to the integration of the EU series. The T-Y results clearly indicate that EU prices are the Granger cause for UA prices. The null hypothesis stating that UA prices do not Granger-cause the EU prices was not rejected at the 5% significance level. This justifies adoption in formulas 1 and 2 UA prices as the Y_t variable and EU prices as the X_t variable.

Subsequently, different versions of the ARDL(p,q) model (Eq. 1) were estimated (taking into account the deterministic components, the number of lags and the estimation method). According to the Bayesian information criterion (BIC) the suggested model is the ARDL(2,3), according to the Schwarz information criterion (SIC) it is the ARDL(6,3), whereas using the AIC criterion indicates the ARDL(9,9). The aforementioned models are suggested regardless of the set of deterministic components. Due to the fact that all models estimated via an OLS suffer heteroscedasticity problems it was decided to use the Newey-West HAC estimator.

The residual autocorrelation was tested by the Breusch-Godfrey LM test. The ARDL(2,3) model (which is a very parsimonious model) suffers from the serial autocorrelation for the 4-6 week span. No such problem was found for the other models, thus it was decided to use the ARDL(6,3) model suggested by the HQ criterion, which is a compromise between the AIC and SC criteria. Subsequently, the ARDL-ECM(6,3) model was estimated with different sets of deterministic components (Table 3).

The applied bound co-integration test confirmed the existence of a statistically significant long-run equilibrium relationship between the UA and EU prices. In all the models, the calculated F statistics are over the upper bound critical value at the 1% significance levels. Relying on the ARDL-ECM models, the long-run equilibrium relationships were estimated (Table 3). In the long-run a 1% increase in EU sunflower oil prices causes an increase in sunflower oil prices in Ukraine ranging from 0.91% (the model with the unrestricted constant and the restricted trend) to 1.00% (the model without a constant). The results also indicate that after the shock the Ukrainian sunflower oil prices are adjusting to the long-run equilibrium at a rate of 5.5-6.2% per week. Kuts and Makarchuk (2020) using monthly price series and Engle-Granger co-integration test also confirmed the long-run equilibrium relationship between UA and EU sunflower prices. Employing that methodology they also obtained the long-run equilibrium relationship coefficient (0.98) which is similar to ours and confirmed the Granger causality from EU to UA prices.

We ignored the multicollinearity of variables in estimated ARDL-ECM models as most researchers do. In theory, multicollinearity only increases the parameter uncertainty while coefficients are still unbiased. In our case (these concerns models estimated for the whole sample as well as models with structural breaks), strong multicollinearity measured by Variable Inflation Factors (VIF) takes place only for variables on levels while there is no such problem for differenced variables (see formulas 1 and 2). This is understandable because cointegrated variables are also correlated which results in a high VIF. However, the possible further transformation

Variable	No const.	Unrestricted const.	Unrest. const. and rest. trend
d_UA(-1)	0.243***	0.243***	0.245***
d_UA(-2)	-0.010	-0.009	-0.006
d_UA(-3)	-0.035	-0.034	-0.031
d_UA(-4)	0.049*	0.050*	0.053*
d_UA(-5)	0.105***	0.106***	0.111***
d_EU	0.190***	0.187***	0.188***
d_EU(-1)	0.182***	0.181***	0.179***
d_EU(-2)	0.142***	0.142***	0.140***
EU(-1)	0.055***	0.053***	0.056***
UA(-1)	-0.055***	-0.056***	-0.062***
C	-	0.019	0.033**
Trend	-	-	6.06E-06**
Description	Bound co-integration test		
F Stat.	20.394	21.158	15.649
CV 10%	I(0)=2.44 I(1)=3.28	I(0)=4.04 I(1)=4.78	I(0)=4.05 I(1)=4.49
CV 5%	I(0)=3.15 I(1)=4.11	I(0)=4.94 I(1)=5.73	I(0)=4.68 I(1)=5.15
CV 1%	I(0)=4.81 I(1)=6.02	I(0)=6.84 I(1)=7.84	I(0)=6.10 I(1)=6.73
Coint. Eq.	UA=1.00*EU	UA=0.95*EU	UA=0.91*EU + 0.0001*TREND
Lag	Breusch-Godfrey serial correlation LM test (F stat)		
4	1.839	1.915	2.099*
6	1.540	1.636	1.830*
8	2.038**	2.134**	2.263**

Source: the authors' study

Table 3: ARDL-ECM(6,3) estimated model and bound co-integration test.

of the model given by formula 2 (estimated and presented in tables 3, 5, and 6) by replacing Y_{t-1} and X_{t-1} with the error correction term (ECT) eliminates this problem with the rest coefficients being unchanged. This shows that the coefficient estimates of the ARDL-ECM models seem to be robust to the problems of heteroscedasticity.

In ARDL models, the evaluation of autocorrelation is crucial for the quality of the model. Errors of estimated models are not serially correlated for lags up to 4, but there are problems with the correlation for lags greater than 6 weeks (Breusch-Godfrey LM test). The increase in the number of lags in models only reduces the autocorrelation up to the order of the applied lags. Autocorrelations for higher orders are still significant. This also suggests that the coefficients of the ARDL-ECM model may change over time. This supposition seems to be confirmed by the CUSUM test for squared residuals suggesting structural breaks in coefficients or in volatility.

Time-varying price transmission

Taking into account possible changes in the strength of price adjustments due to factors discussed in the introduction, it was decided to apply several versions of the Bai-Perron test for multiple structural breaks at an unknown point. Testing has an advantage over the subjective determination of the moments of structural changes, because it takes into account all known and unknown factors influencing the price transmission. These tests were applied to the ARDL (6,3) models with different sets of deterministic components. It was assumed that all the independent variables may cause structural changes (thus their coefficients may change over time) and residuals in different sub-periods may have different distributions. These assumptions allow us to determine different price transmission regimes arising from changes in price levels, the speed of response of market agents as well as price risk. Table 4 shows the results for the application of different variants of Bai-Perron multiple breakpoint tests at the 5% significance level. These results significantly differ depending on the type of the test used and assumed deterministic components. It needs to be emphasized here that in all the cases the structural change was detected for 2014.

In the further part of the study two models with constants were estimated. One model assumed three structural breaks, while the other contained

5 structural changes (see bolded break dates in Table 4). Coefficients of estimated unrestricted (conditional) ARDL-ECM models (Equation 2) as well as results of bound co-integration tests are presented in Tables 5 and 6. The tables also include results of the ADF unit root and T-Y Granger causality tests in particular subsamples. For these tests, the optimal number of lags was newly determined based on the AIC. Since none of the time series in individual sub-periods is integrated of order two, it is possible to use the ARDL models.

In the first presented model (Table 5) we have four sub-periods that differ significantly from each other. Until 2006, UA was exporting little sunflower oil to the EU. Nevertheless, due to the international trade and information flows the prices of sunflower oil in Ukraine and in the EU were co-integrated. In 2006-2010, sunflower oil prices were highly volatile due to increasingly active biofuel policies and the economic crisis. As a result, sunflower oil prices in UA and the EU in 2006-2010 are characterized by a lack of co-integration at the significance level of 5%. This is the only period, in which we deal with bidirectional Granger causality. In the other sub-periods, the prices in Ukraine adjusted to those in the EU and not the other way around. In 2010-2014, there was a further increase in price linkages. Since 2014, along with the saturation of the biofuel market and the fall in world crude oil prices, the long-run price linkage has weakened.

The price adjustments in the model with 5 structural breaks are slightly more complex (Table 6). Here, we are dealing with two bidirectional Granger sub-periods: 2000-2003

B-P test variant	No constant	Constant	Constant + trend
L+1 vs. L sequentially determined breaks	3/31/2006, 30/7/2010, 14/11/2014*	**29/9/2006, 05/11/2010, 14/11/2014**	07/3/2014
L+1 vs. L globally determined breaks	31/3/2006, 30/7/2010, 14/11/2014	11/4/2003, 29/9/2006, 05/11/2010, 14/11/2014	18/4/2003, 29/06/2006, 17/12/2010, 14/1/2014
1 to M globally determined breaks: sequential F-statistic	25/4/2003, 29/9/2006, 30/7/2010, 07/3/2014, 21/4/2017	**25/4/2003, 29/9/2006, 09/7/2010, 07/2/2014, 03/3/2017**	18/4/2003, 12/5/2006, 17/7/2009, 07/2/2014, 03/3/2017
1 to M globally determined breaks: highest significant F-statistic	25/4/2003, 29/9/2006, 30/7/2010, 07/3/2014, 21/4/2017	25/4/2003, 29/9/2006, 09/7/2010, 07/2/2014, 03/3/2017	18/4/2003, 12/5/2006, 17/7/2009, 07/2/2014, 03/3/2017
1 to M globally determined breaks: UDmax	07/3/2014	07/3/2014	07/3/2014
1 to M globally determined breaks: WDmax	07/3/2014	25/4/2003, 29/9/2006, 09/7/2010, 07/2/2014, 03/3/2017	18/4/2003, 12/5/2006, 17/7/2009, 07/2/2014, 03/3/2017

Note: *Dates: day/month/year
Source: the authors' study

Table 4: Break dates in the ARDL(6,3) model according to Bai-Perron multiple breakpoint tests (HAC estimation).

Time span	2/2000-9/2006	9/2006-10/2010	11/2010-11/2014	11/2014-7/2020
Variable	Model coefficients			
d_UA(-1)	0.470***	0.406***	0.020	0.151
d_UA(-2)	-0.049	-0.075	0.029	0.043
d_UA(-3)	0.210***	-0.138*	0.031	-0.083
d_UA(-4)	-0.113**	0.134**	-0.010	0.040
d_UA(-5)	0.041	0.157**	-0.077	0.166***
d_EU	0.068*	0.294***	0.270**	0.053
d_EU(-1)	0.070**	0.265***	-0.005	0.092
d_EU(-2)	0.128***	0.104*	-0.017	0.054
EU(-1)	0.049***	0.129*	0.111***	0.234***
UA(-1)	-0.051***	-0.120**	-0.090***	-0.280***
C	0.014	-0.074*	-0.148**	0.324*

Source: the authors' study

Table 5: The ARDL-ECM(6,3) model with 3 breaks (HAC estimation) (to be continued).

Time span	2/2000-9/2006	9/2006-10/2010	11/2010-11/2014	11/2014-7/2020
Description	Bound co-integration test			
F Stat.	14.603	4.010	7.292	11.288
CV 10%	Restricted const. I(0)=3.02 I(1)=3.51 / Unrestricted const. I(0)=4.04 I(1)=4.78			
CV 5%	Restricted const. I(0)=3.62 I(1)=4.16 / Unrestricted const. I(0)=4.94 I(1)=5.73			
CV 1%	Restricted const. I(0)=4.94 I(1)=5.58 / Unrestricted const. I(0)=6.84 I(1)=7.84			
Coint. Eq.	UA=0.96EU	UA=1.07EU	UA=1.24EU	UA=0.83EU
Lag	Breusch-Godfrey serial correlation LM test (F stat)			
4	0.871			
8	0.744			
Variable	ADF test statistics			
UA	-2.051	-1.689	0.204	-3.091**
d_UA	-7.386***	-4.612***	-13.791***	-7.435***
EU	-1.448	-1.881	-0.440	-2.391
d_EU	-17.946***	-3.598***	-7.376***	-16.924***
Independent var.	Toda-Yamamoto causality test statistics			
UE	6.662***	7.751***	3.674**	15.294***
UA	1.772	3.446**	1.393	1.873

Source: the authors' study

Table 5: The ARDL-ECM(6,3) model with 3 breaks (HAC estimation) (continuation).

and 2006-2010. Additionally, in 2014-2017 the UA sunflower oil prices are a Granger cause for EU and not the other way around. In this period, the coefficient for the long-run relationship was only 0.33. This model, similarly to the model in Table 5, also confirmed the lack of price co-integration in 2006-2010 at the 5% significance level.

Interpretation of price adjustments was facilitated by the use of cumulated Impulse Response Functions (IRF) (see Figure 2). These charts show the percentage response of Ukrainian prices to a 1% change in EU prices for the models estimated in Tables 5 and 6. In the following paragraphs, when discussing the possible reasons for the change in the speed and strength of price transmission, and hence the sunflower oil market integration, we will mainly refer to the model with 5 structural breaks.

From the Figure 2, it can be seen that in the years 2000-2010 the strength of Ukrainian price adjustments to EU prices was gradually increasing. It concerned both the short-run price adjustments as well as the long-run price transmission. This may be explained by the gradual surge in sunflower oil exports to the EU caused mostly by the increased demand for vegetable oils in the EU related to the biofuel policy. In 2000-2010 total sunflower oil import from Ukraine to the EU increased 40-folds – from \$ 16 million to \$ 644 million (Comtrade 2020). At the same time, EU biodiesel production increased 13.6 times. Thus, it can be noted that the reduction of the Differential Export Tax on sunflower seeds by Ukraine from 23% to 13% (see Shmygol et al., 2013; Tulush and Hryshchenko, 2018) at that time did not have any significant impact on reducing the competitiveness of Ukrainian sunflower oil exports.

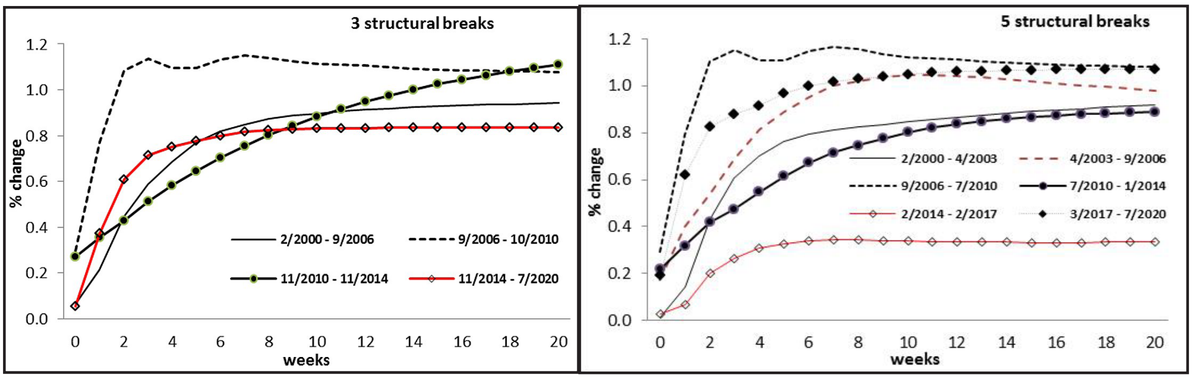
In 2006-2010, the short-run price adjustments between UA and EU sunflower oil prices were the strongest. It was the period of the so-called biofuel boom during which many European Union countries were not able to meet the requirements set by the European Commission in the field of biofuel blending rates. As a result, the import demand for vegetable oils in the EU significantly increased (Comtrade 2020). In the light of the EU-28 Biofuels Annual Report (USDA-FAS 2020), sunflower oil constitutes only 2-5% of feedstock used for biodiesel and renewable diesel production in the EU. Although sunflower oil is hardly used for the production of biofuels, it is an excellent substitute for rapeseed oil or palm oil. Hence, the situation on the sunflower oil market and the horizontal transmission of prices between UA and EU are also strongly dependent on the biofuel policy in the European Union.

The combination of many events caused the price transmission to decline in the period from July 2010 to February 2017. Of which the weakest price links were observed from February 2014

Time span	2/2000-4/2003	4/2003-9/2006	9/2006-7/2010	7/2010-1/2014	2/2014-2/2017	3/2017-7/2020
Variable	Model coefficients					
d_UA(-1)	0.582***	0.361***	0.411***	0.551***	0.094	0.059
d_UA(-2)	-0.129	0.085	-0.077	-0.162	0.059	0.003
d_UA(-3)	0.089	0.353***	-0.140*	-0.100	0.013	-0.040
d_UA(-4)	-0.055	-0.188***	0.142**	0.163**	0.046	0.064
d_UA(-5)	0.049	-0.039	0.159**	-0.072	0.151	0.046
d_EU	0.015	0.174**	0.291***	0.218**	0.027	0.192
d_EU(-1)	0.076**	0.123*	0.285***	-0.074*	-0.077	0.252**
d_EU(-2)	0.179***	0.020	0.097	0.033	0.024	0.093
EU(-1)	0.044***	0.045***	0.131**	0.073***	0.127**	0.203***
UA(-1)	-0.046***	-0.048***	-0.122***	-0.081***	-0.380***	-0.189***
C	0.012	0.016	-0.078	0.063	1.716***	-0.081
Description	Bound co-integration test					
F Stat.	6.565	6.004	3.327	6.677	6.154	7.845
CV 10%	Restricted const. I(0)=3.02 I(1)=3.51 / Unrestricted const. I(0)=4.04 I(1)=4.78					
CV 5%	Restricted const. I(0)=3.62 I(1)=4.16 / Unrestricted const. I(0)=4.94 I(1)=5.73					
CV 1%	Restricted const. I(0)=4.94 I(1)=5.58 / Unrestricted const. I(0)=6.84 I(1)=7.84					
Coint. Eq.	UA=0.96 EU	UA=0.95 EU	UA=1.08 EU	UA=0.90 EU	UA=0.33 EU	UA=1.07 EU
Lag	Breusch-Godfrey serial correlation LM test (F stat)					
4	1.712					
8	1.392					
Variable	ADF test statistics					
UA	-1.528	-2.735*	-1.675	-3.348**	-4.538***	-2.079
d_UA	-6.719***	-5.239***	-4.546***	-3.947***	-9.335***	-11.638***
EU	0.904	-2.110	-1.952	-1.962	-2.465	-2.341
d_EU	-12.228***	-13.383***	-3.555***	-10.273***	-13.401***	-7.496***
Independent var.	Toda-Yamamoto causality test statistics					
UE	6.652***	3.213***	7.138***	4.505***	0.115	16.330***
UA	3.078**	1.762	3.061***	0.550	5.143***	1.390

Source: the authors' study

Table 6: ARDL-ECM(6,3) model with 5 breaks (HAC estimation).



Source: the authors' study

Figure 2: Cumulated impulse response functions for the ARDL(6,3) models with 3 and 5 structural breaks (%).

to February 2017 (see the model with 5 structural breaks). Firstly, the pressure on the use of biofuels of the first generation in the EU decreased significantly after reaching the minimum levels of biocomponents in liquid fuels. Environmental policy and the reorientation from the production of 1st generation biofuels towards 2^{nd} and 3^{rd} generation biofuels are of key importance here

(USDA-FAS 2020). As shown by the data (OECD/FAO 2020), biodiesel production from vegetable oil in 2000 accounted for 99% of biofuel production in the EU, in 2011 it reached 95%, while in 2019 it was only 78%.

Secondly, it coincided with a significant drop in crude oil prices in the world markets in 2014, which reduced the competitiveness of biofuels in relation to conventional fuels. At that time, there were more and more doubts about the economic efficiency of biofuel production as compared to conventional fuels. The political turmoil in Ukraine (the annexation of Crimea in 2014 and the devaluation of the Ukrainian currency) in Ukraine also contributed to the weakening of the relationship between UA and EU prices. It can be concluded that the increase in commercial risk (the possibility of delivering goods under the conditions of possible port blockades) and the exchange rate risk, or the limitation of production opportunities as a result of the occupation of part of Ukraine by Russia or separatist troops was of significant importance for the weakening of the spatial integration of UA and EU sunflower oil markets. This is also confirmed by the stagnation in the export of sunflower oil from Ukraine to the European Union in 2010-2015 (Comtrade 2020).

Since 2017, there has been a noticeable increase in sunflower price transmission between Ukraine and the European Union. The signing of Deep and Comprehensive Free Trade Area (DCFTA) between the EU and Ukraine in 2014 which led among others to remove customs duties on agricultural commodities was here crucial. The DCFTA has been provisionally applied since 1 January 2016 and the Association Agreement formally entered into force on 1 September 2017 following ratification by all EU Member States. Thanks to it, the average annual value of sunflower oil exports from Ukraine to the EU in 2016-2019 was almost twice as high as in 2010-2015 (Comtrade 2020). Hence, the increase in price integration of analyzed sunflower oil markets in 2017-2020 is accompanied by an increase in the trade flow between Ukraine and the European Union. The situation on the palm oil market may also have contributed to the increase in the integration of the Ukrainian and EU sunflower oil markets. Although the gradual withdrawals of biofuels in the EU with a high risk of indirect land-use change (ILUC) will be implemented since 2021, the EU imposed anti-subsidy duties on palm oil in 2019. This led to a significant drop in palm oil imports in 2019-2020 (Comtrade 2020), which could undoubtedly benefit Ukraine by increasing its exports. Thus, in this period, as a result of changes in the EU trade policy, both the trade creation and trade diversion effects on the sunflower oil market can be seen.

The possible time-varying price transmission between the world and Ukrainian agricultural commodity markets was indicated by Götz et al. (2016). Those authors especially pointed to the time-varying long-run relationship between grain prices in Ukraine and prices worldwide due to the trade restrictions. Also, Hamulczuk et al. (2019) discovered structural changes in the long-run equilibrium relationship between EU and UA rapeseed prices as a result of changes in the VAT reimbursement policy in Ukraine. In our case (sunflower prices), the evolution of price transmission speed (booth long-run relationship and short-run adjustment) and the existence of multiple equilibria are caused by a wide spectrum of factors.

Conclusion

The goal of the paper was to test and present an evaluation of the time-varying integration of UA and EU sunflower oil markets. Estimated ARDL-ECM models for the entire sample confirmed the existence of a long-run equilibrium relationship between the UA sunflower oil prices and the EU prices. In the long-run, a 1% increase in EU sunflower oil prices causes the growth of the UA sunflower oil prices ranging from 0.91% to 1.00%. This confirms the strong integration of these markets in 2000-2020.

However, the Bai-Perron tests confirmed the presence of multiple structural breaks in the estimated ARDL-ECM models. The number of breaks differs between the type of test used and assumed deterministic components. Although it can be concluded from the entire sample that the EU prices are the Granger cause for the UA prices, but in some sub-periods, a bidirectional casualty or causality from the UA to the EU prices may be observed (in 2014-2017).

The estimated ARDL-ECM models with structural breaks allow us to conclude that the short-run and the long-run price adjustments differ significantly over time. Thus, the obtained results confirmed the time-varying integration of the UA and EU sunflower oil markets. Moments of structural breaks and the speed of price transmission may be attributed to various, more or less evident, factors. Factors influencing the price adjustment include trade and biofuel policies, changes in crude oil prices, the appearance of economic crises and the supply-demand situation on the sunflower oil market. Generally, in 2000-2010 the price transmission increased along with the sunflower oil demand pressure (caused by the biofuel policy) and an increase in the world crude oil prices. In 2014-2017, the long-run price linkage has weakened due to the saturation of the biofuel market, the fall in world crude oil prices as well as instable political situation in Ukraine. Along with implementation of the DCFTA an increase in the strength of price transmission and trade flow in sunflower oil between Ukraine and the European Union is noticeable.

In the future further alterations may be expected in the strength of price links, however, it is difficult to clearly assess the direction of these changes. The new legislative proposal for a Renewable Energy Directive (called "RED II") in the EU establishes an upper limit for conventional biofuels, starting from 7% in 2021 and dropping gradually to 3.8% in 2030 (Directive EU 2015/1513). This policy reorientation could reduce the demand for Ukrainian sunflower oil. However, the gradual phasing out of the utilization of palm oil as a feedstock for biofuel production in the EU since 2021 should increase the EU demand for sunflower oil. Moreover, in accordance with the DCFTA, Ukraine agreed to a schedule for decreasing its export duty on sunflower seed exports to all the EU Member States to zero by 2027. This situation may negatively influence the domestic processing capacity due to the growth of the sunflower seed export. Among other factors influencing the development of the UA sunflower production and export opportunities we can list the introduction of possibilities for the buying and selling of agricultural land in Ukraine and guidelines for optimum crop rotations with limits for oilseeds share in the total planted area. The ongoing COVID-19 pandemic is another factor that may influence the integration of global, including EU-UA, oilseed markets.

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Influence of Key Performance Indicators in Marketing on the Financial Situation of Wine Producers Using ICT

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Abstract

Marketing is one of the key elements of the success of all companies, including the wine sector. Given the importance of wine producers for agriculture, it is important to define and monitor key performance indicators in marketing (KPIs) for a successful stay in the market and a competitive position at home and abroad. Today, the increase in competitive advantage includes mainly marketing, innovation and information and communication technologies. New digital tools and innovations have changed the way we approached data and decisions. A modernly adapted and effective strategic marketing strategy represents for wine companies an understanding mainly of their possibilities as well as the possibilities to influence the customer. This article evaluates the key performance indicators in marketing (KPI) and its relationship and impact on the financial situation of wine producers in Slovakia. The research sample includes 80 respondents. We obtained the primary data through a questionnaire, which was filled in by the leaders of wine companies. We verified the accuracy by means of descriptive statistics and multiple linear regression and Kruskall-Wallis test. We have verified the reliability of the data with the Cronbach alpha test. We have formulated scientific assumptions for in-depth analysis: hypothesis 1 – assumes that key performance indicators have a significant influence on financial situation of selected companies, hypothesis 2 – the use of ICT in marketing is statistically related to the key performance indicators.

The results showed a statistically significant impact of KPIs on the financial situation of companies. We have identified significance in customer satisfaction and loyalty, brand awareness and return of investment. However, we were unable to statistically confirm the impact of other indicators (sales growth, market share, gaining new customers). We also identified significant differences in the use of ICT in marketing with key performance indicators in hiring new customers and return on investment. This research contributes positively to the importance of brand building in the eyes of customers as well as customer service, building loyalty and satisfaction, which returns to the loyal approach of customers to the repurchase of wine products and provides advice for professionals. Return on investment helps in more accurate business decisions that can be used when purchasing new equipment (technology), hiring employees, or properly assessing the profitability of marketing strategies.

Keywords

Marketing, key performance indicators, ICT, loyalty, wine producers.

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Introduction

Time has witnessed significant changes in marketing and marketing strategies. Over time, various trends have emerged in sustainability, social needs and consumer behavior. The reassessment of various issues and phenomena has resulted in a new direction in marketing strategies (Kumar et al., 2012). Marketing strategy describes how a company will fulfill marketing activities and decisions through which it will create and maintain a competitive advantage (Varadarajan et al., 2001). It also focuses on ways to differentiate itself from its competitors, making maximum use of its specific advantages to deliver the best possible added value to customers in the business environment (Jain et al., 2012). The focus on the consumer has also been confirmed Charter et al. (2006), which reflects changes in customer requirements and expectations. It confirms that companies should react flexibly and adopt different strategies in order to gain a competitive advantage in the market. Moreover, advertising messages should be tailored based on specific segment characteristics (Šedík et al., 2019). Ferrell and Hartline (2007) also highlight the importance of activities related to maintaining good relationships with employees and supply chain partners. Šimek et al. (2008) adds that in the case of any long-term relationship, the basic pillar is based on mutually beneficial cooperation. Therefore, the choice of the right strategic marketing procedure is often a decisive factor for the successful growth of the company's performance. With the advent of technological progress and innovation, there has been a growing interest among professionals to access documentation that would bring up-to-date measures in marketing activities that could have an impact on improving the financial performance of companies. Grønholdt and Martensen (2006) addressed key marketing performance measures and developed a quality list of the most valuable measures. There is also a discussion in the marketing literature about the constant emphasis on assessing the financial responsibility of marketing functions in companies (O'Sullivan et al., 2009; Grønholdt and Martensen; 2006; Rust et al., 2004; Gotteland et al., 2020). It is desirable to point out the impact of marketing and marketing decisions on key business results and return on investment. Despite this trend, there are still companies on the market that work with data that often misnames and transforms data into inappropriate indicators. On the other hand, few companies know that it is necessary to monitor key success indicators in particular. In this context, managers should have knowledge of the right indicators of success for today's market requirements. According to Badawy et al. (2016) there are 4 ways to measure performance indicators:

1. key result indicators - brings information on the achievement of a perspective or critical factor,
2. result indicators - provide information on the work performed and tasks completed,
3. performance indicators - brings information's that contain things that companies must do,
4. key performance indicators - bring advice to the company on exactly what to do to improve performance.

Empirical studies demonstrate different approaches to key performance indicators in different directions. Granberg and Munoz (2013) identified 5 areas for action to quickly obtain information if a process does not meet the required standard. Elshakour et al. (2013) came up with the 10 most important KPIs, which include profitability, quality of service and work, growth, customer satisfaction, financial stability, cash flow, market share, security, business efficiency and planning efficiency. Khalifa and Khalid (2015) developed a set of strategic key performance indicators to monitor and improve performance in the tertiary sector. And many other studies (Peng et al., 2011; Diamantini et al., 2013; Keck and Ross, 2014; Ning et al., 2011; Stefanovic, 2014; Suryadi, 2007; An et al., 2004) provide important information and findings about KPIs in the areas of business, education, or information technology. At the heart of these studies is knowledge for companies to improve organizational efficiency by identifying metrics that contribute to long-term success. Greve (2011) considers in performance to be a key influence on the strategic direction of managers. It states that the indicators of sales growth in the target market is a criterion for managers to assess the relative position of the company in relation to competitors and, to some extent, to re-evaluate their marketing strategy. Berg (2017) combines sales growth with competitiveness. It notes that market share helps managers assess primary and selective market demand. It also adds that market share allows to assess not only the overall growth or decline of the market, but also trends in customer selection, which can have a significant impact on the financial situation of the company. There may also be a situation where the market is highly homogeneous, and customers face their indecision in distinguishing between products and their quality. In this case, the cost of detailed information about possible product differences may be too expensive or require time for in-depth analysis, and therefore companies must use the external success factor as brand awareness, which can be a decisive factor in purchasing (Shaw, 1981). This was confirmed by an extensive study by Warlop et al. (2005), which pointed out that, in specific circumstances, brand awareness is closely linked to a company's better market performance. Wangenheim and Bayón (2004); Anderson and Sullivan (1993) state that the constant fulfillment of customer needs leads to their satisfaction, which increases customer loyalty, and this leads to an increase in the company's reputation. The positive relationship between customer satisfaction and loyalty has been demonstrated by several studies (Mittal and Kamakura, 2001; Anderson and Sullivan, 1993). Customer loyalty is linked to the frequency of more frequent purchases, which provide increased revenue and an improved financial situation (Homburg and Fürst, 2005). Last, but not least, return on investment (ROI), which can have a positive effect on performance. This is based on the research of Krizanova et al. (2019), who pointed out that the return on investment is used as a standard metric for evaluating investments in communication tools. Petriľák et al. (2020) state that due to the increased bargaining power of customers, more and more companies are trying to adapt new business techniques as well as innovations in the form of technologies to more effective strategic management. Hallová and Hanova (2019) confirm that the use of specific information and communication technologies significantly increases the precondition for the success of companies in economic activity.

Material and methods

The article analyzes practical indicators that examine the overall performance of the company in relation to the primary goal of companies, achieving financial stability, especially in the agricultural wine sector. The main goal is to analyze the impact of key performance indicators in marketing (sales growth, market share, gaining new customers, brand awareness, customer satisfaction and loyalty, return on investment) and their potential in business development. The research focuses on the financial situation of wine producers in Slovakia, as well as the use of information and communication technologies in marketing. The article is the result of internal specific research conducted at the Department of Informatics, Faculty of Economics and Management, SPU in Nitra.

The research was based on a descriptive-analytical method using convenient sampling to achieve the objectives of the study. The research sample consisted of 80 companies, represented by middle and senior management from all wine-growing areas in Slovakia. Several scientific methods were used to evaluate the questionnaire. We used the method of analysis and comparison to identify the current state of KPIs and the use of ICT in marketing. We used the method of synthesis to clarify new and previously undefined relationships and patterns from the used literature. We used the induction method to create hypotheses in which we came to the essence of the phenomenon and the formulation of conclusions. Furthermore, the method of deduction allowed us to derive new statements more accurately, where we tested whether the chosen hypotheses are able to explain the investigated fact. The questionnaire survey was compiled electronically via Google Forms and data were collected and processed via MS Excel, in which basic tables and graphs were processed. Statistical processing and evaluation were performed via IBM SPSS software. The questionnaire covers all dimensions of independent and dependent variables that allow the testing of hypotheses. However, based on the obtained results, we first used Cronbach alpha to measure the internal consistency, which ensures the validity of the design of the questionnaire as a tool for data collection.

Scope of reliability analysis		Variables	Cronbach's alpha
All variable items	H1	7	0.778
Variables to Hypothesis H1		6	0.731
All variable items	H2	7	0.712
Variables to Hypothesis H2		6	0.731

Source: own research and processing

Table 1: Internal Consistency Coefficients (Cronbach Alpha).

As the Table 1 shows, testing the reliability of the questionnaire data was sufficient for the selected hypotheses. As stated by Sekaran and Bougie (2010) the reliability may be (0.60) or higher to indicate adequate internal consistency. The characteristics of the research sample include the legal form of the business, the size of the business, the years of existence of the winery and the vineyards regions (Table 2).

Formulated hypothesis was tested using statistical method multiple linear regression, which is used to predict a continuous dependent variable (financial situation) and several independent variables (key performance indicators), as well we also used nonparametric Kruskall-Wallis test. During testing hypothesis, if p-value is lower than significant level, in case of IBM SPSS, its 0.05, than null hypothesis is rejected and alternative hypothesis confirm. To achieve deeper analysis of research objectives, we defined following hypotheses:

Hypothesis 1 – We assume that key performance indicators have a significant influence on the financial situation of selected companies.

Hypothesis 2 – The use of ICT in marketing is statistically related to the key performance indicators.

Variable	Category	Number	Percentage %
Legal form	Private limited company	51	63.75%
	Self-employed farmer	6	7.50%
	Joint stock company	7	8.75%
	Cooperatives	6	7.50%
	Special forms of ownership	2	2.50%
	Self-employed person	8	10.00%
Size of company	micro company (0-9 employees)	47	58.75%
	small company (10-49 employees)	33	41.25%
Years of existence	1-5 years	13	16.25%
	5-10 years	20	25.00%
	more than 10	47	58.75%
Location	Little Carpathians Wine Region	34	42.50%
	South Slovak Wine Region	17	21.25%
	Nitra Wine Region	12	15.00%
	East Slovak Wine Region	4	5.00%
	East Slovak Wine Region	9	11.25%
	Tokaj Wine Region	4	5.00%

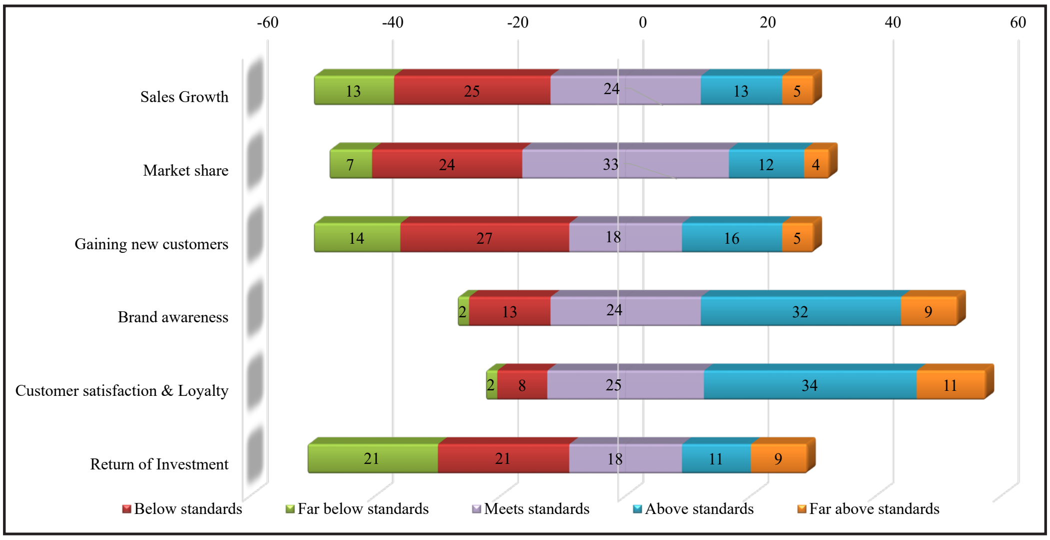
Source: own research and processing

Table 2: Description of study sample according to the demographic variables.

Results and discussion

The questionnaire survey was focused on companies in the field of wine production. The reference sample consisted of 57 micro-enterprises and 33 small enterprises, which evaluated their key indicators of marketing performance, the general financial situation, and the implementation of ICT in marketing activities. The following section focuses on the analysis of financial, market and customer-oriented indicators. We also study the use of ICT in selected companies.

The results of the survey showed several interesting findings. If we look at Figure 1, there is a disproportion between some indicators - the customer-oriented area, 51% - 54% of companies achieve above-standard results in awareness of their brand and customer satisfaction and loyalty. It is important to note that these are mainly companies with a 5–10-year existence. From this we can assume that companies apply mainly processes that put the customer



Source: own research and processing

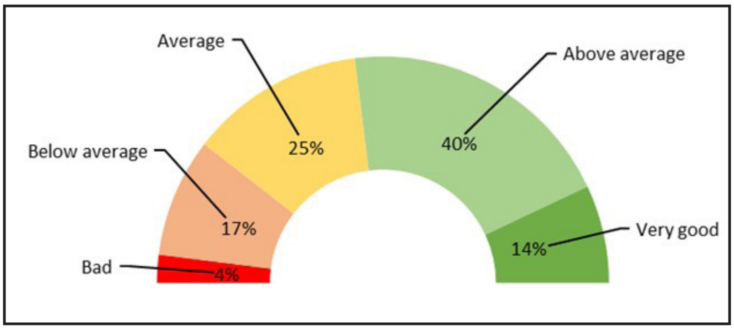
Figure 1: Evaluation of the key performance indicators of wine producers.

at the centre of their activities. In areas focused on finance (sales growth, return on investment) and the market (gaining new customers, market share), the percentage of companies is worse and does not meet the required standards.

Each of the above indicators requires overcoming different challenges and meeting the set goals. It is the managerial approach to marketing that defines the areas of measurement and results, and, among other things, the ability to integrate business functions, match supply and demand and transform them into purchasing processes, as well as generate financial and non-financial results. Part of our survey was also to find out the financial situation of wine producers. We asked companies to assess the financial situation for the last 3 years on a scale from 1 to 5 (where 1 reflected bad financial situation and 5 very good financial situation). As we can see from Figure 2, for half of the respondents the financial situation of wine producers is somewhere between above average and very good. Only 21% of respondents do not achieve the expected financial results.

KPIs are very important for planning, control, information support, creating transparency and support for decision-making in management (Meier, Horst, et al., 2013). In order to determine the impact of selected KPIs on the financial situation, we created a model that is linked to the first hypothesis. We used multiple linear regression to test hypothesis 1, and the results are shown in Table 3. It shows the impact of KPIs (sales growth, market share, gaining new customers, brand awareness, customer satisfaction and loyalty, return on investment) on the financial situation of wine producers. The regression model provided a high degree of fit, which was also reflected in the correlation values R (0.769), R^2 (0.592), which states that the relationship between the variables is at the level of 76%, which is generally considered a strong effect size. In addition, the value of R^2 indicates a prediction of 59% of the financial situation from KPIs. In other words, for each unit increase in KPIs, there is a prediction of a 59%-unit increase, i. e. improving the financial situation. Based on these results, the null hypothesis should be rejected, and the alternative hypothesis accepted.

Table 3 shows that brand awareness, customer satisfaction and loyalty, and return on investment have a statistical effect (p-value less than 0.05) on achieving the adoption of the above KPIs to improve the financial situation. On the contrary, sales growth, market share and the acquisition of new customers did not have a statistically significant effect.



Source: own research and processing

Figure 2: Evaluation of financial situation of wine producers.

Dependent Variable	R	R Square	F Change	df1	df2	Sig.	β	T	Sig.
Financial situation	.769[a]	0.592	17.659	6	73	0.001			
			Sales Growth				-0.11	-1.265	0.21
			Market share				0.08	0.872	0.386
			Gaining new customers				0.06	0.684	0.496
			Brand awareness				0.28	3.181	0.002
			Customer satisfaction & Loyalty				0.55	5.963	0
			Return of investment				0.18	2.069	0.042

Source: own research and processing

Table 3: Multiple Regression Coefficients.

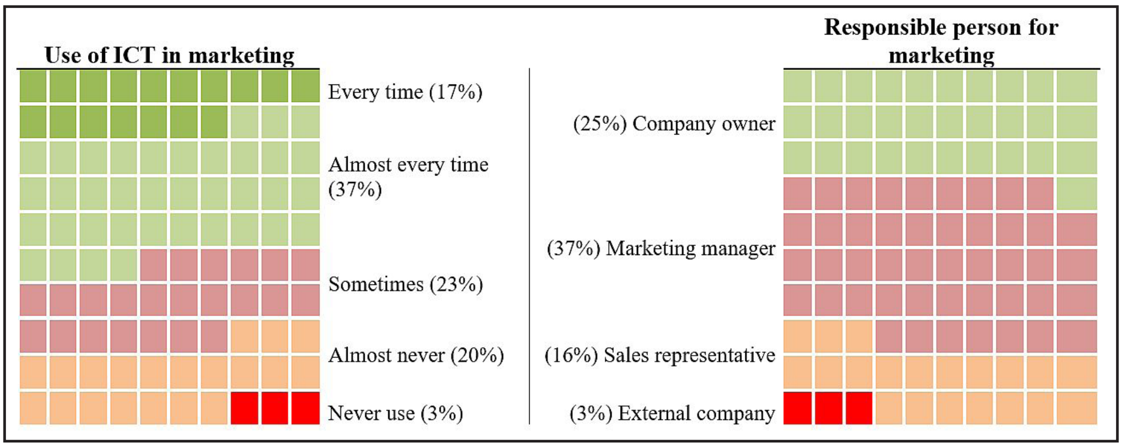
Ailawadi et al. (2003) revealed the same metrics with our customer-oriented results - recommendation, awareness and satisfaction that were effective in all managers' decisions. Consistent use of these metrics significantly improves results in the decision-making process. The presented study also matches with the findings of Mintz et al. (2020), who confirm the use of tools that monitor effective metrics of customers' mind-set. They were proven to be associated with achieving better performance results, which, however, depend on the employee (manager), the company, the type of industry and, of course, the way of deciding on the marketing mix. There is also a consistency between the results of the current study and the findings of Farris et al. (2015), in which the return on investment has a positive impact on the present value of future profits and meets the criterion of financial success.

As mentioned above, the questionnaire also focused on the evaluation of ICT in marketing. Figure 3 presents the results, which reflect the frequency of the use of ICT in marketing by wine producers in a visual comparison with the area of management and responsibility for the marketing department.

The results showed us that for more than half of wine producers, the use of ICT is an integral part of marketing processes. We have noticed this fact in companies where ICT is used by a marketing manager. On the other hand, 23% of companies do not use the potential of ICT in marketing. Here we found out that the marketing officer was the owner of the company, where we assume that he is in charge of a number of other responsibilities such as vineyard management, ethnological activities, wine sales and other influences such as insufficient investment solutions, lack of time or inexperience. Today, ICT and innovation play a very important role and are used to implement business action plans and strategic goals that can shift business performance. Hypothesis 2 was tested to determine whether there is a statistically significant relationship between the use of ICT supporting marketing activities and selected KPIs. Based on the results of the nonparametric Kruskall-Wallis test, we can say that there are at least 2 differences in the use of ICT with a statistically significant difference in KPIs, namely in gaining new customers (p-value 0.029) and return on investment (p-value 0.020), which support accepting the hypothesis 2. We can also state that the other KPIs did not differ statistically and are therefore normally distributed. It is necessary to mention that for statistically significant values we analysed their averages, where we confirm the difference in the use of ICT, on the other hand, more frequent use of ICT did not have a significant positive effect on the performance of indicators.

Conclusion

To fill the gap between the empirical effectiveness of metrics and the normative system, we proposed a statistical model to evaluate the use of individual KPIs and the financial situation of wine producers. In contrast to our statement Poláková et. al. (2015) argues that, in general, there is no universal set of indicators that companies should monitor. However, if the company correctly estimates the mentioned metrics for measuring marketing activities, their implementation can be transferred to the company's financial indicators, which will lead the company to long-term sustainability



Source: own research and processing

Figure 3: Frequency of use ICT in marketing and responsible person for marketing.

and transform it into the modern concept of Society 5.0. Our statistical model assumes that the effectiveness of indicators will differ based on companies' decisions about the current marketing mix as well as the settings of processes that responsible employees select in the belief that they are the most effective. The main contribution of the research is to provide relevant information to improve business in the field of agro-sector of wine production for the right direction of businesses. The results of the model provide us with several important insights into the use of key performance indicators in marketing. We found out that 3 KPIs - brand awareness, customer satisfaction and loyalty, return on investment - are effective for wine producers to improve their financial situation and we recommend applying them in the decision-making processes of the marketing mix. The effects of increased use are based on attracting new customers as well as achieving repeat purchases, increasing interactivity with customers and their personalization, as well as helping for more accurate business decisions. Similar research was conducted in 2020, where Mintz et. al. (2020) came to similar conclusions, adding that customer-focused metrics are more accessible to managers (1), (2) they have a significant impact on decisions and their goals, (3) they lead to improved results in the decision-making process, (4) they are easy to understand and (5) they have the potential to build long-term profitability. On the other hand, with the current marketing mix settings, the other three metrics - sales growth, market share and customer acquisition - do not have a significant impact on improving the financial situation, so it is desirable to find more effective metrics or make changes to the marketing mix settings. These results therefore provide us with evidence supporting the orientation of wine producers mainly to the customer. Furthermore, information and communication technologies can be a major driver in business. However, the integration of ICT in marketing can vary considerably across companies. It is crucial to choose appropriate strategies to explore and seize the opportunities that ICT creates. Our research confirmed the different use of ICT in marketing for wine producers, but we cannot confirm whether the use and adaptation of ICT in business increases the performance of selected indicators. Despite the benefits and significance of this study, there are some limitations that open several doors for future research. Based on this, we would recommend replicating research on multiple samples, using multiple indicators to analyse it, applying research to multiple areas of the agro-sector and regions, and finding out the relationship between ICT, innovation, entrepreneurship, and business performance.

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Possibilities of Using Social Networks as Tools for Integration of Czech Rural Areas - Survey 2021

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Abstract

This paper deals with the use of social networks in agricultural enterprises and focuses mainly on their role and share in increasing the competitiveness of agricultural enterprises in the market. Primary data were obtained from an extensive survey of the development of information and communication technologies in agricultural enterprises, which was conducted in the first quarter of 2021 throughout the Czech Republic ("Survey 2021"). The research was primarily focused on capturing current trends in the use of ICT with emphasis on selected key areas (broadband, social networks, communication tools, regional Internet portals, used hardware categories, used software, mobile communications, Internet of Things, data storage and security, social networks, etc.).

This survey builds on previous extensive surveys conducted by the Department of Information Technologies, Faculty of Electrical Engineering, CULS in Prague in several phases since 1999, with the last stage being conducted in 2017. Some surveys were conducted in cooperation with the Ministry of Agriculture of Czech Republic.

Compared to recent years, the survey includes new domains, such as the use of the Internet of Things in plant and animal production, data storage and security, the impact of the Covid-19 pandemic on the company's core operations, etc. The survey was prepared, conducted and administered by the Department of Information Technology, Faculty of Economics and Management, University of Life Sciences Prague.

Keywords

Social network, Facebook, agricultural activity, non-agricultural activity, business, marketing, online communication, rural area.

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Introduction

Today, social networks are used by almost everyone and almost every day, and therefore it is a very effective marketing tool. This article links this new trend to the specific environment of rural areas.

The social network acts as a bridge providing active communication with a selected target group, with whom it is difficult to establish communication (Kánská et al., 2011). Social media has thus become an integral part of the marketing strategy of many companies around the world and in recent years has literally expanded into all industries. The funds devoted to this type of marketing activity are rising sharply, as are the number of companies involved in communication and promotion on social networks. The Internet has become a transmitter for the further rise and development of social networks aimed at different groups of users. Internet social media overcomes one of the biggest limitations - a connection to a certain place (place of business, residence, etc).

The Covid-19 pandemic has swept the world in recent months. The depth and duration of the economic crisis caused by the coronavirus pandemic will affect not only our way of life but also the future of many businesses. And this crisis has only helped people look for brands they can trust and that contribute to their safety. People want to be assured that "their" brands have the situation with their suppliers under control, are transparent and trustworthy. This is largely due to customers' efforts to avoid malls for fear of becoming infected with the virus. But the key lesson is that users know where to turn. In times of crisis, they look for what they know, whether a product or a service.

In the Czech Republic, social networks are still partly perceived as a tool for private interpersonal communication and not as a marketing tool. However, the number of companies using social networking as a source of information or to aid public promotion has skyrocketed in recent years. Therefore, it is very interesting to examine this extension of the marketing life cycle within farms (Marquardt et al., 2011) and (Bittner and Müller, 2011).

Social media

People have been socializing for millenia, but thanks to the Internet, the possibility of establishing contacts online in virtual places has arisen. Over the last few years, various social networks have been developed on different platforms such as Twitter, YouTube, Facebook, Linkedln and many more. Over time, these began to become an integral part of everyday life. Thanks to the possibility of creating connections with other people, these media allow us new social opportunities, which may include making new contacts, expressing feelings, normal communication, creating one's own career and sharing interesting things from life (Eger, 2015). According to Safko and Brake (2009), social media are all web networks that mediate online communication between their users, and this communication includes the sharing of opinions, information and knowledge. Griner (2009) has a similar approach to social networks, describing them as a digital tool for building an online network across users and sharing information between them. Whereas, according to Boyd (2007), social networks are defined as: "A web service that allows individuals to create a public or at least partially public profile within a defined and limited higher system. A social network is formed by a set of sub-users who share a common interest. "According to this definition, various types of profiles are created on social networks, which are needed for communication between users. Kaplan (2010) defines social media a little differently. According to him, social media is a group of Internet applications that enable the creation, sharing and modification of user content, which are created in technology based on Web 2.0. Where Web 2.0 is an environment that allows each other to communicate and create and share content between users in a virtual world. Harris (2009) explains how social media works, and thus defined five basic functions for their use: to log in, rate, view, comment, and create. Currently, there is a wide field of social media, which differ according to the focus of networks and functions. According to Kozel (2011), social media can be divided as follows:

- social networks (Facebook, Myspace, Linkedln),
- blogs, videoblogs, microblogs (Twitter),
- discussion forums, Q&A portals (Yahoo! answers),
- wikis (Wikipedia, Google Knol),
- social education systems (Digg, delicious, Jagg, Reddit),
- shared multimedia (YouTube, Flickr),
- virtual environments (Second Life, The Sims).

Social networks are becoming an indispensable part of the functioning of individuals, companies and modern society as a whole. Today, a total of 3.4 billion users use social networks, which is almost half of the world's population. Social networks have been around for many years, but the first major milestone was the founding of Facebook in 2004. Social networks have undergone tremendous development in those 16 years. Hundreds of projects have emerged that have sought to gain market share and innovate in digital communications and user interaction. The number of users on the Internet has doubled since 2010, and another one billion new users are expected to join next year. And most of them join social networks. The further development of social networks is therefore almost guaranteed in the coming years. (Nets in a handful, 2020)

Providing a suitable broadband communication infrastructure is the basis for the use of all modern Internet technologies and applications, including social media. Social media is evolving very fast and makes extensive use of multimedia content, which is closely related to the requirements for high quality connections. Rural areas generally face significant connectivity problems (including connection availability), especially connection quality. These problems have been monitored and analyzed by the Department of Information Technology for a long time and are addressed, for example, in the following papers: (Jarolímek and Vaněk, 2003) and (Vaněk et al., 2008) and (Šimek et al., 2014).

Social media users

It can be stated that social media is an artificial platform of "general knowledge", where an event or product can be highly valued. (Cardoso and Espinosa, 2020).

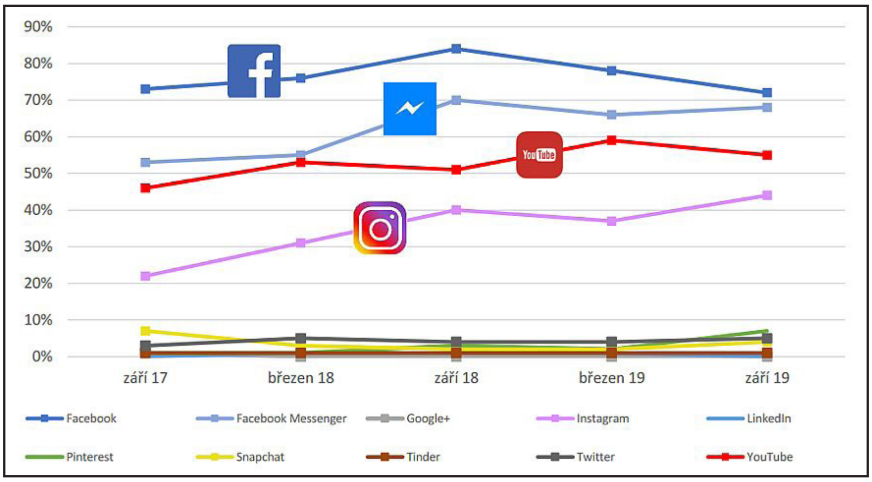
Facebook (the most widespread social network in the Czech Republic) began to be an effective tool when it exceeded the so-called critical limit. This limit represents at least a 15% share of the social networking market. Registered users have exceeded the critical limit, and user numbers have not stopped growing, resulting in higher popularity. Figure 1 clearly shows that Facebook is still the number one network in the Czech Republic, followed by YouTube and Instagram. (H1, 2020)

Facebook users are influenced by their lifestyle and similarly by their friends. As well as sites that are very popular among target groups, social networks integrate the presentations of many companies including those which focus on agriculture and agricultural products. (Satin-Hernandez and Robinson, 2015).

Trends on social networks in the Czech Republic provide an overview of daily usage across social networks in the Czech Republic for the 15-25 age group. In the autumn of 2019, the daily usage of this target group on Facebook was 72%. This is twelve percentage points less than in the same period in 2018, but Facebook is still the most effective in this respect. (H1, 2020)

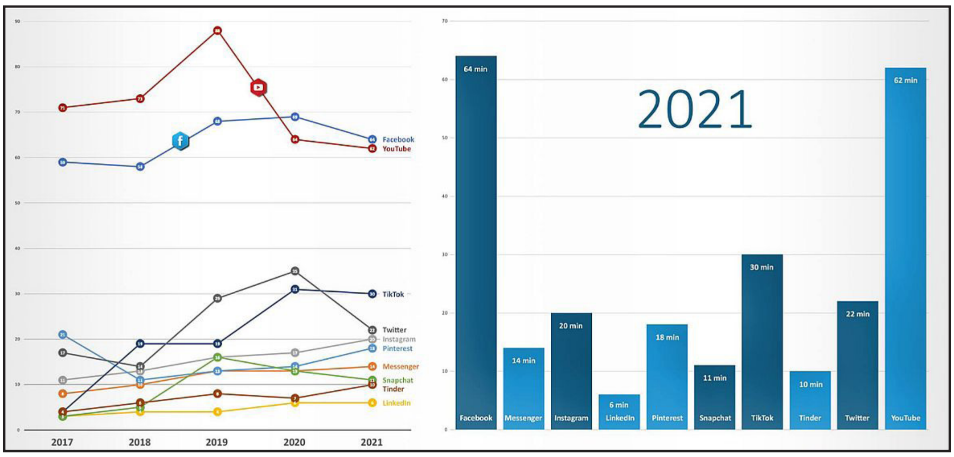
At the same time, however, there is a noticeable increase in usage on Instagram and that of YouTube. The values for these two platforms follow a growing trend. In 2020, the share of daily usage on Instagram can be expected to grow, to the detriment of Facebook. Despite this fact, it is still true that the young group is still best reached by advertisers on Facebook. See Figure 1.

Facebook is often referred to in marketing agencies as a social network that is slowly declining. However, the statistics do not correspond to this, see Figure 2. Czechs spend 64 minutes a day on Facebook, and 62 minutes on Youtube. This chart



Source: H1.cz

Figure 1: Social network trends in 2020.

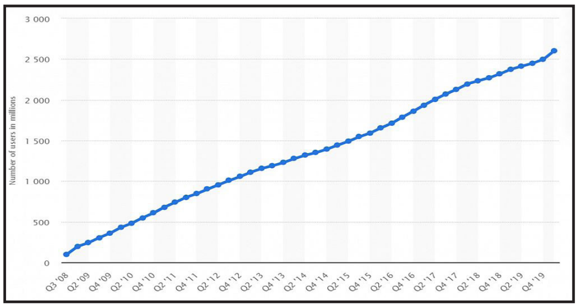


Source: H1.cz

Figure 2: How much time do users from Czech Republic spend on social networks (minutes).

demonstrates the tremendous power of Facebook, and any advertising investment on Facebook will pay off quickly in the form of user awareness of the product or brand.

Facebook had over 2.6 billion active monthly users, as of Q1, 2020. This makes it the biggest social networking site in the world. Also, the number of users almost doubled in the last five years, clearly indicating that it is still popular and relevant, see Figure 3.



Source: Statista.com

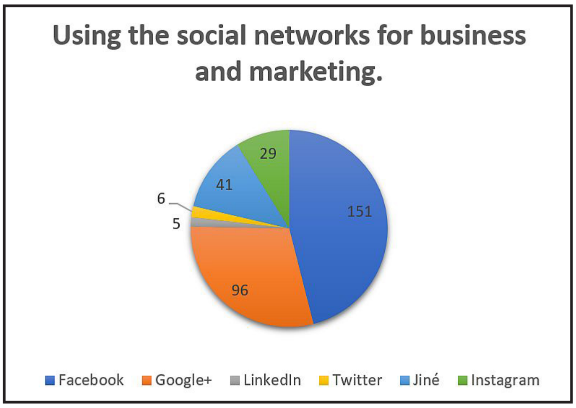
Figure 3: Facebook users per day.

Materials and methods

In the spring of 2021, an online questionnaire survey was conducted on the development of information and communication technologies (ICT) in agricultural production enterprises, which covered the entire territory of the Czech Republic. For the first time, the paper form of the questionnaire was dropped entirely. The survey mainly addressed companies that manage at least 100 ha of arable land. The aim was to focus on agricultural enterprises from a comprehensive perspective on the development of ICT, which can be observed especially within larger enterprises. More than 700 questionnaires were collected. The survey focused on the current state and development of ICT, including related issues such as internet connection, internet use, mobile communications, the use of IoT and social media, and last but not least the impact of the COVID-19 pandemic in this area. In general, the use of social media, the acquisition of information for business activities and the impact of coronavirus measures on the operation of the company were analyzed.

Results and discussion

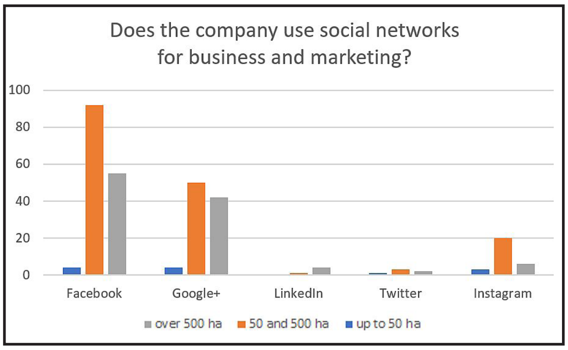
The survey shows that the target group actively uses social networks. Business and marketing were cited as reasons for using the social networks. The types of social networks used according to the answers drawn from Survey 2021 are shown in Figure 4.



Note: This question was answered by 239 respondents.
In the „other“ answer, respondents most commonly replied that they are using social networks but did not want to specify which ones or for what purpose.
Source: Own processing.

Figure 4: Using the social networks for business and marketing.

Figure 5 illustrates, which companies use social networks for business activities. The most active are those enterprises that farm on 50 - 500 ha of arable land. This confirms that the digital divide in these companies is being reduced by the usage of social networks. Companies use them to their advantage with regards to the promotion and establishment of new contacts with customers or suppliers.



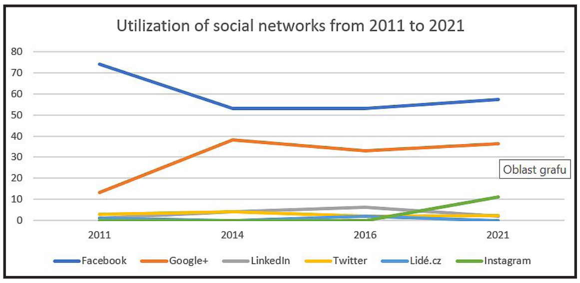
Source: Own processing.

Figure 5: Does the company use social networks for business and marketing? (separated by area of arable land).

A categorization into three groups of enterprises based on area of arable land was chosen for a certain broader view of the given issue: up to 50 ha, 50 - 500 ha and over 500 ha, which also corresponds to the UTIPA methodology (User-Technological Index of Precision Agriculture) (Jarolímek et al., 2017).

Figure 6 shows the development of the use of social networks in agricultural enterprises in 2011, 2014, 2016 and 2021. The graph shows a significant decline in Facebook in 2014 and 2016. A possible explanation is that new networks have appeared on the market. (Tinder, TikTok), which were discovered and used for a shorter period of time. Furthermore, in the years of decline, Facebook was more of a social network for the 20-30 age group. Now, after about 8 years, users are older and are still connected to groups that benefit them in the form of knowledge about new products, etc. In 2020, the use of Facebook skyrocketed again. The explanation for this increase in the use of Facebook is the pandemic situation in the Czech Republic and in the world. As mentioned in the Introduction chapter, Facebook seemed to be a lesser-used medium at one point, but it can be assumed that the coronavirus pandemic situation has returned Facebook to the forefront and businesses have begun to present themselves via Facebook to reach a new part of their target audience.

In general, this has led to a shift towards social networks that are well-known and established themselves over longer time period. This was a way to connect with the world of friends, business, new contacts and information about new products. The first usage of Instagram social network by agricultural companies has been a recorded in 2016. Overall, the graph suggests that the use of social networks is still in the growth phase.



Source: own processing

Figure 6: Utilization of social networks from 2011 to 2021 in rural areas.

Social networks are used primarily for company public presentation, secondly for corporate communication and, last but not least, as a source of information.

With the development of the information society and the continuing adoption of ICT, attention is also shifting towards electronic information sources in the agricultural and rural environment. This trend will continue on an ongoing basis. The problem of the so-called "digital divide" is gradually being overcome.

It can be seen from Figure 8 that most information is obtained by agricultural holdings from the Internet. This is followed by the professional press and the experience of colleagues (best practices). Social networks are a source of information with respect to suppliers, organizations or colleagues. Large players in the agricultural machinery market have been reducing investments in paper leaflets for a long time and are betting on Facebook and Instagram - thus on the good experiences of other colleagues and immediate acquisition of news before the season directly from the source or through industry portals.

From the results of the survey shown in Figure 7, the general hypothesis of increasing usage of the Internet as a basic source of information was confirmed. The Internet is regularly used by companies with a demonstrable dependence on the size of the company, see Figure 8 (the largest ones use it the most regularly, etc.). If the Internet is not used as a source of information on a regular basis, it is used at least occasionally – the number of companies that do not use internet at all is negligible.

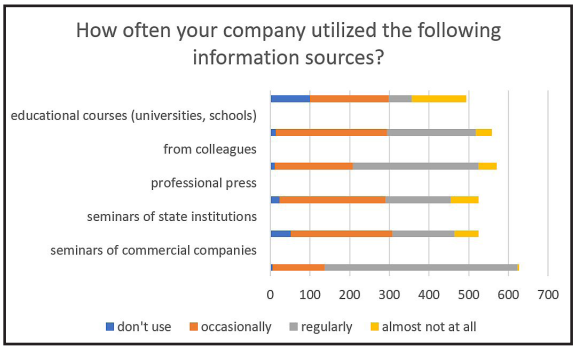


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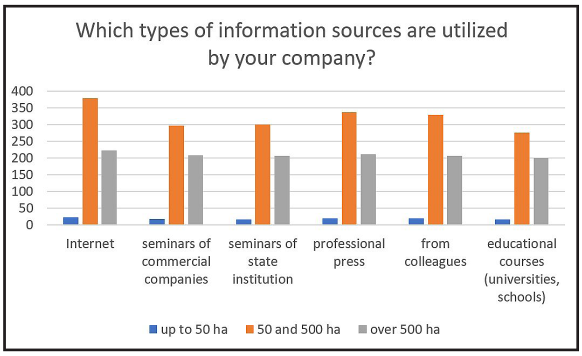
Figure 7: How often your company utilized the following information sources?



Source: own processing

Figure 8: Information sources utilized by agricultural companies (separated by area of arable land).

Impact of the coronavirus pandemic on the use of ICT in agriculture (in rural areas)

Social networks in rural areas make a significant contribution to reducing the digital divide. Users of social networks can access the necessary information, not only within more types of networks, but also more interest groups. In general, farm employees can be considered conservative in using new technologies to improve and simplify their own work, as well as in promoting and establishing new contacts that could direct employees closer to modern technologies and use them to their advantage (more customers, promotion of your own brand, etc.).

The questionnaire survey also examined which statements the individual companies identify with regard to the COVID-19 measures. The results show that the coronavirus pandemic has affected the functioning of companies only partially or not at all. In summary, COVID-19 most influenced communication with customers and suppliers, which began to be more organized using online tools, see Figure 9.

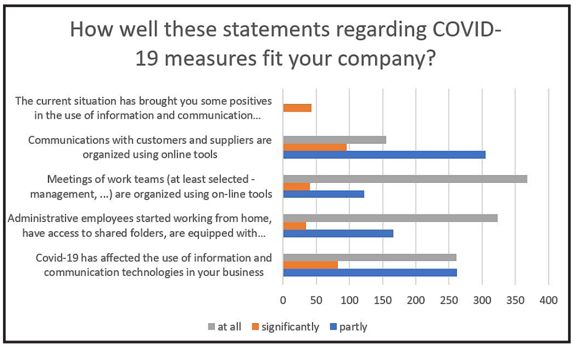


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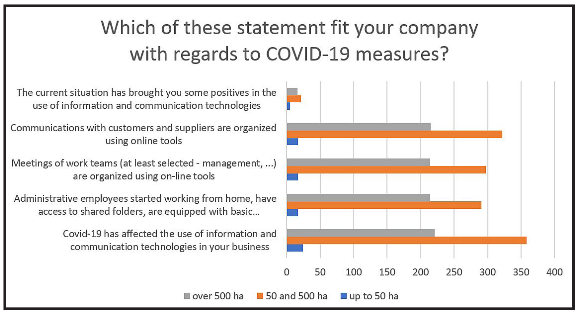
Figure 9: How well these statements regarding COVID-19 measures fit your company?

Figure 10 confirms that farms with more than 50 ha of arable land have been able to respond more quickly and flexibly to changes resulting from the coronavirus pandemic.



Source: Own processing

Figure 10: Which of these statement fit your company with regards to COVID-19 measures? (separated by area of arable land).

Conclusion

In rural areas, it is the people themselves who start and promote digitization projects and work with professional actors from outside. These innovators see digitization as a chance to solve rural problems, such as limited mobility, declining community interactions, demographic change or the digital divide between urban and rural areas. (Zerrer and Sept, 2020)

According to Albar and Houque (2019), the adoption of information and communication technologies (ICT) will enable local SMEs to participate in the European market. Relative benefits, top management support, culture, regulatory environment, capability for Innovation by the owner / manager and ICT knowledge have a significant impact on the overall adoption of ICT in SMEs, while compatibility, complexity and competitive environment have no significant relationship to ICT adoption.

The Department of Information Technology has experience from its own practice that most suppliers and processors limit investments in paper leaflets, etc., but purposefully use social networks and contacts of selected groups on social networks for their promotion or recruitment of new employees.

The further development of social media marketing offers a number of interesting questions for further publishable outputs and subsequent research in the coming years, as the development of social networks is closely linked to the development of customer acquisition strategies.

The authors of the paper will continue to monitor the development of social networks in this specific domain and expect a steady upward trend in the use of social media in agricultural enterprises for both agricultural and mainly non-agricultural activities.

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Asymmetry in Price Transmission: Evidence from the Wheat-Flour Supply Chain in Russia

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Abstract

Price volatility has serious implications for economic welfare of various agents in the grain supply chain. The paper examines asymmetric price transmission along the wheat producer-processor supply chain in Russia using log-transformed monthly prices during the period of 2000-2019. Having specified linear asymmetric vector error correction model, we exposed the long-term cumulative asymmetry in price transmission, however, the hypothesis of short-term symmetry presence failed to reject. The analysis revealed dominant position for wheat producers and wholesalers over the wheat processors. Imperfect competition and their resulting market power, as well as the existence of a huge number of illegal processors are the main causes for asymmetric price transmission on the Russian wheat market.

Keywords

Price transmission, asymmetry, grain market, Russia, food.

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Introduction

The grain market is the largest agricultural market in Russia. Grain is one of the key products for both food industry and livestock companies.

Russian grain production exceeds domestic consumption and thereby orients on export. Over the past five years the volume of grain production has shown steady positive growth dynamics mainly due to the existence of favorable weather conditions for the main grain crop - wheat. More than third of grain produce is exported, although, increasing the grain export potential is limited by the insufficient level of logistics infrastructure development. Exporters purchase as well as change in the exchange Russian ruble rate effect significantly on the grain pricing in Russia.

In the contrast, Russian flour production has been declining for several years on end. Since 2013, the production volume has not exceeded 10 million tons. Moreover, since 2015 production has been steadily reducing to 9.4 million tons in 2018. Export possibility can really be a good support for the industry. However, Russian flour export does not match the competitors in price. Russia's share in the world flour trade does not exceed 2 %, that is less than the share of Turkey, Kazakhstan, Argentina and Ukraine put apart. In order to compete efficiently on the world flour market government support measures are required. Flour producers have the perception that there is price disparity and the price changes are not efficiently transmitted through farmer-processor supply chain.

Prices play an important role in a market economy. Price volatility has serious implications for economic welfare of various agents in the food supply chain, and therefore, it is worth studying vertical price transmission to provide recommendations for policymakers. The presence of asymmetric price transmission (APT) tends to be characteristic of market imperfection resulting from a various reasons. The examination of APT can provide information indirectly about the income distribution amongst the different levels of a vertical supply chain which is of high importance in the area of welfare analyses (Szőke et al., 2019). Price transmission analysis in the aspect of asymmetries presence is a key determinant of food security, especially in emerging markets such as Russian.

There exists a large literature on price transmission in agro-food sectors. Most of the literature on price transmission in the cereals markets relies on multiple regressions of lagged price differences as well as linear or non-linear modeling to identify asymmetric price relationships.

Brümmer et al. (2009) used a Markov-switching vector error-correction model (MSVECM) to model multiple regime shifts in the relationship between wheat and wheat flour prices in Ukraine. The analysis revealed four regimes whose timing coincides with political and economic events in Ukraine. Although causality ran both ways, this suggested that much policy intervention in response to shocks to Ukraine's wheat and flour markets might have increased rather than reduced instability. Cinar (2018) examined the price volatilities in Turkish cereal markets by means of the Baba-Engle-Kraft-Kroner (BEKK) version of the multivariate Generalized Autoregressive Heteroskedastic (MGARCH) method. His findings of the BEKK MGARCH model provided evidence that there was a one-way, strong and permanent volatility spillover from the corn and barley market to the wheat market. Hassouneh et al. (2017) studied producer and consumer wheat prices in Slovenia having applied a threshold vector error correction and multivariate generalized autoregressive conditional heteroscedasticity model with exogenous variables. Results indicated that price-level adjustments mainly favour retailers by increasing their marketing margins.

Wu et al. (2019) tested the asymmetry of vertical price transmission in two Nigerian cowpea markets with using the autoregressive distributed lag model and asymmetric error correction model. Results suggested that price transmission in one market is symmetric, but it is asymmetric in another. Ricci et al. (2019) analyzed vertical price transmission in two typical Italian wheat chains, the pasta and bread chains. The authors detected the evidence of asymmetric price transmission having applied a co-integration methodology. Haile et al. (2017) assessed the degree of vertical price transmission along the wheat-bread value chain in Ethiopia by applying a vector error correction model and an impulse response analysis on the base of monthly price data. The empirical findings indicated that price changes were not transmitted efficiently as well as significant co-integration and causal relationships existed between prices at the different market stages. Rumankova (2014) used vector error correction model and impulse-response analysis to defend a(symmetrical) nature of price transmission along the Czech wheat agro-food chain. Usman and Haile (2017) investigated producer-retailer price transmission on the two Ethiopian major cereal markets with using specific asymmetric error correction models. They gave evidence of asymmetric price transmission for the wheat market in one of the regions, unlike the wheat market in another one, indicating some differential in the quality of infrastructure and the length and complexity of wheat value chains between two markets. Louw et al. (2017) used time series econometric techniques to study vertical price transmission across two value chains in South Africa. Their results indicated full price transmission in the wheat-to-bread chain but incomplete price transmission in the maize-to-maize meal chain. Symmetry in price adjustment was not rejected in both chains. Liu et al. (2012) estimated the elasticity of farm-gate prices to retail ones for twelve major products (incl. wheat), having specified linear regression models with two proxies (infrastructure level and population density in Chinese provinces). The authors found strong linkages between retail and farm-gate prices that have continually been intensifying since the policy retrenchment period in 1995.

Taking into account the significant changes of the food sector in emerging markets, the need to get insight into magnitude, speed, asymmetry of price transmission as well as factors behind price transmission, is as reasonable as ever. There exists certain gap in the research literature on vertical price transmission, as well (a)symmetries presence in the Russian grain supply chain, that this paper seeks to feel. The purpose of the paper is to expose price transmission features and evaluate the asymmetric price transmission in the Russian wheat market (i.e., from farm-gate to the wholesale market) by means of the most popular econometric models and reveal the causes of asymmetries.

Materials and methods

Our price transmission study has been carried out using monthly observations related to average nominal prices for wheat, wheat flour at the farmer and processor levels from January 2000 to December 2019 in Russian Federation. The number of observations is sufficient, that is desirable since the larger sample, the more robust our results are. The source of the data is the Federal State Statistics Service of Russia (available online at **http://www.gks.ru**). We use the logarithmic transformation of monthly prices measured in Russian rubles per ton in order to compute price elasticities and mitigate price series fluctuations. Transformation allows the results to be interpreted in percentage change terms.

Firstly, we run preliminary tests to identify price series features and then the empirical model will be specified and estimated. Wheat and flour price relationships are investigated by means of multiple linear regression analysis.

Regressing non-stationary time series can lead to spurious regression thereby having resulted in model misspecification. In order to identify the unit root presence, we ran Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and KPSS tests (Kwiatkowski et al., 1992). ADF test specifies the null hypothesis that the price series is non-stationary, i.e. unit root is present.

To test the non-stationarity of price series the ADF test uses following regression:

$$P_t = c + \beta t + \alpha P_{t-1} + \sum_{i=1}^{k} \psi_i \Delta P_{t-i} + \varepsilon_t \quad (1)$$

where P_t – log-transformed price, c – intercept, t-linear time trend. This regression includes k lagged first differences to account serial correlation.

KPSS test assumes the null hypothesis (H0): stationary time series versus alternative (Ha): non-stationarity in time series. The KPSS test offers a complement to the ADF test to intensify econometric inference.

The number of the optimum lags was chosen based on the Akaike (1973) information criterion (AIC).

As a next step, we should test our time series for cointegration. Often time series behave similarly over time and have same stochastic trend. Such time series are considered co-integrated. In that case we obtain super-consistent OLS-estimates for the model parameters. Granger (1981) introduced the cointegration technique. Then the cointegration concept was followed up by Engle and Granger (1987), Johansen (1988), Johansen (1991), Johansen (1995), Phillips and Ouliaris (1990), Gregory and Hansen (1996) and Hatemi (2008).

In order to check the price series and determine the cointegrating rank we applied the Johansen methodology (Johansen, 1991; Johansen, 1992) based on maximum likelihood estimation. Unlike some of the tests, it avoids the issue of choosing a dependent variable. In order to determine the number of cointegrating vectors, Johansen has proposed two different likelihood ratio tests: the trace test and the maximum eigenvalue test shown below in the equations 2, 3 respectively. The tests also generate maximum likelihood estimates of the parameters in a vector error-correction (VEC) model of the cointegrated time series.

$$LR_{(r,n)} = -T \sum_{i=r+1}^{n} \ln(1 - \check{\lambda}_i) \quad (2)$$

$$LR_{(r,r+1)} = -T \ln(1 - \check{\lambda}_{r+1}) \quad (3)$$

where $LR_{(r,n)}$ is the likelihood ratio statistic for testing whether rank $(\Pi) = r$ versus the alternative hypothesis that rank $(\Pi) \leq n$; $LR_{(r,r+1)}$ is the likelihood ratio test statistic for testing whether rank $(\Pi) = r$ versus the alternative hypothesis that rank $(\Pi) = r + 1$; n is the number of variables; r is the number of cointegrating relationships; T is the sample size; $\check{\lambda}$ is the i-th largest canonical correlation; Π is the coefficient matrix obtained from the VAR model, where $\Pi = \alpha\beta'$, α are known as the error correction terms in the vector error correction model (VECM) and each column of β is a cointegrating vector in the long run.

The likelihood ratio statistics do not have the conventional χ^2 distribution. Asymptotic critical values are given by Johansen and Juselius (1990). If two tests provide contradictory results, we are going to rely on trace statistic since it tends to have superior power in empirical studies (Lutkepohl et al., 2001).

Our dataset is based on monthly observations, a seasonal component is reasonable to be taken into consideration as well. The approach that helps to reveal seasonal unit roots was developed by Hylleberg et al. (1990). However, in order to produce robust and better results HEGY test needs a rather long time series (30-60 years), otherwise, that would bias estimation results since "asymptotics" works, taken into account number of years, not the number of observations. More observations would also make it possible to explore seasonality in seasonal VECM parameters. Unfortunately, we have less than 20-years price series. There are some problems with seasonal cointegration interpretation, especially for assymetric price transmission analysis. We use piecewise linear cointegration methods (AVECM), which are based on the assumption that at any given time price transmission follows one of two linear error correction regimes. In the Assymetric VECM, for example, prices follow one of two linear error correction processes depending on whether positive or negative deviations from the long-run equilibrium relationship are being corrected (wheat price decreased in the summer-autumn, and opposite in the winter-spring).

The cointegrating price series have error correction model representation as a special case of Vector Autoregression (VAR) models. The modeling of asymmetric price transmission can be classified into precointegration and cointegration techniques (Meyer and von Cramon-Taubadel, 2004; Frey and Manera, 2007). VECM has become the 'workhorse' model in analyzing asymmetric price transmission, and which adequately represents time series behavior in the presence of non-stationarity and cointegration (Hassouneh et al., 2012). In order to take into account asymmetric adjustments, assymetric VECM (AVECM) alternative have been proposed by decomposing variable first differences and error correction terms into positive and negative components (Granger and Lee, 1989; von Cramon-Taubadel, 1998).

In our study we specify linear AVECM which can be defined as follows:

$$\Delta P_t^{out} = c + \sum_{i=1}^{k} a_i^+ D_{t-i}^+ \Delta P_{t-i}^{out} + \sum_{i=1}^{l} a_i^- D_{t-i}^- \Delta P_{t-i}^{out} + \sum_{j=1}^{m} \beta_j^+ D_{t-j}^+ \Delta P_{t-j+1}^{in} + \sum_{j=1}^{n} \beta_j^- D_{t-j}^- \Delta P_{t-j+1}^{in} + \varphi^+ ECT_{t-1}^+ + \varphi^- ECT_{t-1}^- + \varepsilon_t \quad (4)$$

where, Δ is the difference operator; P_t^{out} and P_t^{in} are the logarithms of the output (wheat or flour prices) and input (wheat or flour) prices respectively; c is the constant; D_t^+ and D_t^- are the dummy variables indicating the sign of the lagged price variables P_t^{out} and ΔP_t^{in} (to capture asymmetry, the dummies are used when wheat (flour) prices increase or fall respectively); $ECT_{(t-1)}^+$ and $ECT_{(t-1)}^-$ are positive and negative error correction terms obtained as the residuals from the long-run relationship between price variables, equal to $ECT_{t-1}=P_{t-1}^{out}$- $\widetilde{\alpha_0}$- $\widetilde{\alpha_1}$ P_{t-1}^{in}; ε_t is a vector of i.i.d random errors.

The optimum lag length is defined in accordance with the AIC and the Schwarz-Bayesian (1978) information (BIC) criterions as a result of VAR modeling. To detect the presence asymmetric price transmission, we apply F-tests for linear restrictions via the following null hypotheses:

H_0: $\varphi^+ = \varphi^-$, the speed of adjustment to the long-run equilibrium is symmetric;

H_0: $\beta_j^+ = \beta_j^-$, distributed lag effect symmetry in price transmission magnitude at each lag;

H_0: $\sum_{j=1}^{m} \beta_j^+ = \sum_{j=1}^{n} \beta_j^-$, cumulative symmetry of all lags.

Asymmetric price transmission between our two time series is evaluated using open-source package "apt" in the econometric software "R" developed by Dr. Changyou Sun (2016).

Results and discussion

The price development at two levels over the period of 2000-2019 can be observed in Figure 1. Visual plot examination gives the insight about probable price series non-stationarity. As seen from the Figure 1, prices appear to move synchronously with the common upward trend during the period. Therefore, some kind of price transmission with possible long-run relationship might be present.

Taking the econometric techniques described above into account, we get started our analysis with checking the transformed price series in natural logarithms for stationarity. Price series have a changing mean, therefore constant worth being included in the models for unit root tests. (Non) stationarity of the price series has been identified with the ADF and KPSS tests. The highest lag is based on Schwert rule (Schwert, 1989). We defined it as follows:

$$P_{max} = 12 \times \sqrt[4]{\frac{N}{100}} \quad (5)$$

where N is sample size.

To choose the optimal lag order we oriented on the information criterion. Our findings are shown in the table 1. According to the ADF test, the null of stationary log-transformed time series in levels has been rejected for two variables. Testing based on first differences revealed significant test statistics at 1 per cent. KPSS test can be used interchangeably with the ADF test. A key difference from ADF test is the null hypothesis of the KPSS test is that the series is stationary. So practically, the interpretation of p-value is just the opposite to each other. That is, if p-value is < significance level, then the series is non-stationary. Whereas in ADF test, it would mean the tested series is stationary. Therefore, the unit root tests in the table below show that both log-transformed price variables are the same integrated, i.e. I (1).

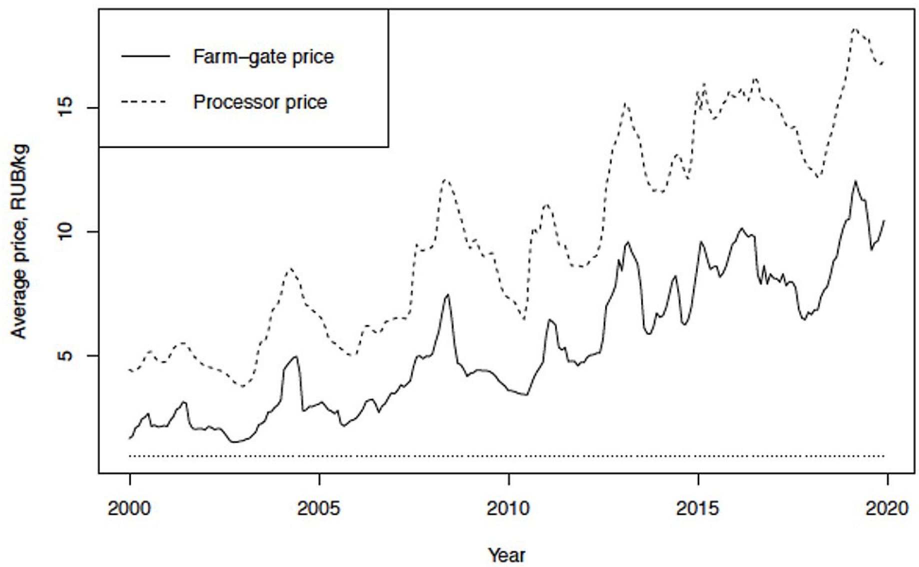
Therefore, as a next step we can perform cointegration test between price pair. Cointegration means that prices move closely together in the long-run, while in the short-run they may drift apart. There might be a linear combination of same integrated price series that is stationary.

Co-integration analysis is used to estimate long-run price relations between non-stationary and same integrated variables.

Given that our price series are I (1), we have run Johansen test to reveal if the non-stationary series are co-integrated. The optimal lag for testing has been selected in accordance with the Akaike information criterion as a result of VAR modeling. As shown in Table 2, we identified one co-integrating equation for farm-processor supply chain.

According to the Johansen test based on the trace and maximum eigenvalue statistics, we can reject the null hypothesis of $r = 0$ and fail to reject the null of $r \leq 1$ at the 1, 5, 10 % significance levels. Therefore, the log-transformed price series are co-integrated and demonstrate long-term relationships with common stochastic trend.

As a result of co-integration between the time series, we are able to specify an asymmetric VECM for the price pair. To avoid autocorrelation problem, heteroskedasticity and autocorrelation-consistent White standard errors have been computed (White, 1980). As seen from the Table 3, statistical model diagnostic revealed that AVECM is well specified since the residuals are normally distributed as well as do not suffer from serial autocorrelation and heteroskedasticity, that is preferable. The ECT coefficients are statistically significant and carry



Source: Federal State Statistics Service of Russia

Figure 1: Current producer prices for wheat and flour in the Russian Federation, January 2000 - December 2019.

Price variable in logarithms	ADF test				KPSS test			
	Lag	Levels	Lag	1st difference	Lag	Levels	Lag	1st difference
FP	7	-1.398	6	-6.122***	14	1.562***	14	0.030
PP	3	-1.494	2	-6.433***	14	1.566***	14	0.025

Note: */**/*** null hypothesis of non-stationarity rejected at 10%, 5% and 1% of significance; FP – farm-gate wheat price, PP – Processor price for flour
Source: own calculations

Table 1: Unit root test results.

Log-transformed price series	Hypothesized number of co-integrating equation	Trace statistics	Max-Eigen values
FP-PP	None (r=0)	42.28***	39.05***
	At most 1 (r≤1)	2.43	3.24

Note: ***/**/* denotes rejection of the null at 1, 5 or 10 % significance level
Source: own calculations

Table 2: Johansen co-integration test for log-transformed price series.

the negative sign, that implies model stability, the convergence to equilibrium and long-term causality from the processor prices to farm-gate ones.

The results from the Table 3 imply that short-run symmetry exists at a given moment in time since the null hypothesis (H_0: $\beta_j^+ = \beta_j^-$) fails to reject at a 5 % significance level. One should pay attention to the sample size choosing a significance level. If the sample size is small (less than 100 observations), it is possible to reject the null hypothesis at a significance level of even 10 %. Our price series are more than 200 observations, hence, we can use 1 % and 5 % significance level. 5 % of significance is a feasible level at which to do empirical research.

However, long-term asymmetry in magnitude changes is available. The null of cumulated symmetry ($\sum_{j=1}^{m} \beta_j^+ = \sum_{j=1}^{n} \beta_j^-$) is rejected at a 5 % of significance. The cumulative positive changes in processor prices are transmitted differently to the changes in farm-gate wheat price in comparison with negative changes in processor price.

The estimation results on the long-term relation between log-transformed FP and PP show that a 1 % change in processor prices leads to 1.21 % change in farm-gate wheat prices. Therefore, we can observe an imperfect market structure. The existence of that market structure in the flour market can be related to the recent developments in Russia. According to information from the Russian union of flour producers in March 2020, grain producers refuse to supply grain to flour mills or make extra high grain prices for the domestic market due to the depreciation of the ruble and the increased export profitability. Moreover, the financial situation in the industry is further getting worse as since 2017 authorized banks stopped concessional lending to the most of flour producers. Now banks refuse to give money for flour mills due to their losses and insufficient level of pledge. That might result in a flour deficit in the Russian market.

Under the current circumstances government support is needed for flour export producers. First, government should compensate export logistics costs (their share in the total costs reaches up to 30%) as well as subsidize the grain price for processors. Among the measures of non-financial support, it is worth mention the promotion of the national brand of Russian flour on the foreign markets. Moreover, the industry needs government support in establishing contacts with key foreign enterprises and distributors. Important measures would be the reduction of logistical barriers for flour exporters. Second, in order to upgrade flour production facilities located near export logistics centers we recommend officials to provide flour processors with concessional loans.

The ECT coefficients representing the long-term relationship take higher value in the upward

	Dependent variable (ΔP_t^{out}) ΔFP_t		F-tests for linear restrictions		
Independent price variables	**Split into positive and negative components** "+"	"-"	$\mathbf{H_0}$: $\beta_j^+ = \beta_j^-$	$\sum_{j=1}^{m} \beta_j^+ = \sum_{j=1}^{n} \beta_j^-$	$\mathbf{H_0}$: $\varphi^+ = \varphi^-$
Intercept (c)	0.029**			5.034**	1.562
ECT_{t-1}	-0.450***	-0.235**		(0.026)	(0.213)
ΔFP_{t-1}	0.258**	0.420***			
ΔFP_{t-2}	0.155	-0.083			
ΔFP_{t-3}	-0.023	0.144**			
ΔFP_{t-4}	0.032	-0.093			
ΔPP_{t-1}	0.345***	0.636**	0.446 (0.505)		
ΔPP_{t-2}	-0.280*	0.117	0.706 (0.402)		
ΔPP_{t-3}	0.004	0.015	0.001 (0.982)		
ΔPP_{t-4}	-0.101	0.667**	3.24* (0.073)		
Adj R^2	0.250		White's test, p-value 0.07		
DW-statistic	2.010		Normality (Doornik-Hansen) test, p-value 0.000		

Note: ***/**/* denotes rejection of the null at 1, 5 or 10 % significance level
Source: own calculations

Table 3: AVECM estimates and F-tests on the coefficients from the model.

direction than in the downward direction. It means that approximately 2.2 (1/0.45) months are required for the farm-gate prices to move towards their equilibrium level when the flour price increases, likewise it takes about 4.3 (1/0.235) months for adjustment towards equilibrium when there is a decrease in the processor prices. Consequently, farm-gate wheat prices converge to equilibrium more slowly in response to the decreases and more quickly to the increases in flour prices at the processor stage. However, the findings of the test indicate that null hypothesis of equilibrium adjustment path symmetry is not rejected.

Conclusion

The paper investigates the asymmetric effects of flour processor price changes on wheat price fluctuations by means of fitting linear AVECM model based on log-transformed monthly wheat and flour processor prices within the period from January 2000 until December 2019 in Russia. Moreover, we obtain long-run parameters of the flour price change effect on the wheat farm-gate price fluctuations. Our study provided empirical evidence as to the existence of long-run asymmetric price transmission within wheat-flour supply chain in Russia that is in line with vast literature on vertical price transmission. Understanding the asymmetric price transmission causes can have considerable welfare and policy implications. Significant reason of asymmetric price transmission on the Russian wheat market is imperfect competition among agents between farms and processing companies and the resulting market power. The grain producers oriented on huge export from Russia may use their market power and react more quickly to increased margins than to the reduced ones. Market power is also highly likely explanation for asymmetric price transmission in the long run. We exposed that wheat market conjuncture gave a dominant position for wheat producers and wholesalers over the wheat processors. The situation for flour producers is worsened by the existence of a big number of illegal processors, producing flour at low prices and selling it to small bakeries, as well as rather weak solvent consumer demand under steady reduction in real incomes. Under the circumstances, legal producers do not have the ability to raise prices, in contrast to wheat producers, and many of them have to operate approximately at the break-even level.

Follow-up study on the wheat-flour asymmetric price transmission can be extended with non-linear modeling and including retail sector in the analysis.

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Price Forecasting Accuracy of the OECD-FAO's Agricultural Outlook and the European Commission DG AGRI's Medium-Term Agricultural Outlook Report

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Abstract

The OECD-FAO's Agricultural Outlook and the European Commission DG AGRI's Medium-term agricultural outlook report provide price forecasts. Users of these forecasts may be interested in their accuracy. This paper measures the accuracy for values forecast for the following year. These are very accurate as regards the AO EU price of poultry, the EC outlook price of common wheat and feed barley, but not so accurate as regards the EC outlookon beef prices. In some cases, discrepancies between the forecasts follow a systematic pattern. The paper also discovers how the OECD-FAO's outlook projections for a common wheat world representative price are changing from year to year. Usually they are positively correlated, but there are certain exceptions where their correlation is significantly negative. This means that the price projections of some commodities may vary dramatically.

Keywords

Outlook, price, forecast, accuracy.

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Introduction

The OECD-FAO's[1] Agricultural Outlook and the EC DG AGRI's[2] Medium-term agricultural outlook report provides a kind of look into the future of the agricultural economy. This includes point forecasts of prices of agricultural commodities. Forecasts might be a useful tool in planning and decision making in agricultural economics and business policy, all of which can be deduced from papers on this topic.

The data forecasting application in agriculture is evaluated ex-post in Brandt & Bessler (1983), with positive results, or widely discussed in Allen (1994) and Bessler (2010). An ex-post evaluation of the OECD-FAO's Agricultural Outlook forecasts is in Rivera-Ferre & Ortega-Cerdà (2010) and Holst (2010), both with not much positive results. The Rivera-Ferre & Ortega-Cerdà (2010) article develops a theory of Stirling (1999) concerning 4 possible states of incertitude and argues that such outlooks assume policy scenarios when they cannot be assumed. This is why they should not be used for policy evaluations. However, users of forecast prices from these outlooks, whether or not for policy evaluation, may be interested in their accordance with the prices that are later considered as realized. Holst (2010) shows on the price of wheat that an autoregressive estimator produces more accurate forecasts than the OECD-FAO's Agricultural Outlook.

Users of the outlook forecasts may also be interested in how much a new edition of an outlook differs from the previous one. If a price forecast differs greatly in comparison with its previous edition, the outlook model assumptions have probably changed, having a significant impact on the price. This will generally discourage dependence on medium-term forecasts of the price because of its high sensitivity to the assumptions. However, it might also mean that the model specifications for the price are incorrect or incomplete and the sensitivity is false. The potential for misspecifications in such a complex model is great, which could be a reason to prefer simple time-series estimators.

[1] The Organization for Economic Co-operation and Development in cooperation with the Food and Agricultural Organization of the United Nations.

[2] The Directorate-General for Agriculture and Rural Development of the European Commission.

The authors therefore measure the correspondence between price projections of different editions of the outlooks. In addition, they also apply some error decompositions that might be helpful for a user of the forecasts in accommodating the differences between projected and realized prices. To simplify the analysis, in most exercises, the authors examine only one-year-ahead forecasts.

Materials and methods

There are two main origins of the data analysed in this paper: firstly, world and EU nominal prices of selected agricultural commodities, published in yearly series of the OECD-FAO's Agricultural Outlook (OECD and FAO, 2009-2019). Selected 7 commodities that the authors of the present paper choose to analyse can be found in Table 1. Secondly, the European Commission's Medium-term outlook report (EC, 2013-2020) yearly EU nominal prices of agricultural commodities, from which the authors choose 10, is also to be found in Table 1.

The OECD-FAO's Agricultural Outlook price forecasts are part of a complex process of Outlook creation, based on a recursive dynamic partial equilibrium AGLINK-COSIMO (OECD and FAO, 2015) model. In most editions of the Outlook, there is one price that is not a forecast. It is an average estimated price from three years preceding the year of publishing of the particular edition of the Outlook. The forecast prices are simply yearly prices, so they are averaged to be comparable to the 3 year realised averages.

The month of publishing is July, and the first year constituting the average begins in the succeeding January (for grains June or July). One might also download yearly realised nominal prices from **https://stats.oecd.org**. These are not part of the Outlook standard publication and their values vary, especially those of meats, where OECD-FAO uses different units of weight. This paper also compares this second alternative to the one with averages as to the accuracy of forecasts.

The EC DG AGRI's price forecasts have a very similar nature to those of the OECD-FAO's Agricultural Outlook, since they are based on the same AGLINK-COSIMO model, yet the overall process of forecasting is different (Enciso,et al., 2015) (Perez Dominguez, et al., 2018). The publishing month is December and this paper assesses the year following the year of publishing.

In almost all exercises, this paper assesses only single-year-ahead[3] forecasts, although the forecast horizon is always up to at least 9 succeeding years. The accuracy would be higher if the forecasts were focused on the publishing year and the following year only, because then there could not be any constraints upon them to be consistent with the forecasts for the following years (the consistency is due to the recursive dynamics of the models).

A complete list of methods used for forecasting assessed prices and years in which these forecasts

[3] So the assessed forecast horizon is one 3 year average (for the OECD-FAO's Outlook) or one year (for the EC's Outlook). For computing the averages, forecasts for the 3 succeeding years are needed.

Referred to as	Full description	Unit	Source
AO wheat	No. 2 hard red winter wheat, ordinary protein, USA f.o.b. Gulf Ports (June/May).	USD/t	OECD-FAO Agricultural Outlook
AO corn	No. 2 yellow corn, USA f.o.b. Gulf Ports (September/ August).	USD/t	OECD-FAO Agricultural Outlook
AO EU beef	EU average beef producer price.	USD/100 kg dw	OECD-FAO Agricultural Outlook
AO EU pigmeat	EU average pig meat producer price.	USD/100 kg dw	OECD-FAO Agricultural Outlook
AO EU poultry	Poultry meat EU average producer price.	USD/100 kg rtc	OECD-FAO Agricultural Outlook
AO butter	F.o.b. export price, butter, 82% butterfat, Oceania.	USD/100 kg	OECD-FAO Agricultural Outlook
AO cheese	F.o.b. export price, cheddar cheese, 39% moisture, Oceania.	USD/100 kg	OECD-FAO Agricultural Outlook
EU wheat	Common wheat (breadmaking quality) price (July/ June)	EUR/t	EC Medium-term outlook report
EU barley	Feed barley price (July/June)	EUR/t	EC Medium-term outlook report
EU maize	Feed maize price (July/June)	EUR/t	EC Medium-term outlook report

Source: own processing

Table 1: List of commodities whose price forecasts are assessed (to be continued).

Referred to as	Full description	Unit	Source
EU sugar	Sugar (white sugar equivalent) price (October/ September)	EUR/t	EC Medium-term outlook report
EU beef	Beef (Young bulls R3) meat price	EUR/t c. w. e.	EC Medium-term outlook report
EU pigmeat	Pig (Class E) meat price	EUR/t c. w. e.	EC Medium-term outlook report
EU poultry	Poultry (Chicken) meat price	EUR/t c. w. e.	EC Medium-term outlook report
EU milk	Milk (farm gate, real fat content) price	EUR/t	EC Medium-term outlook report
EU butter	EU-15 Butter price	EUR/t	EC Medium-term outlook report
EU cheese	EU Cheddar Cheese price	EUR/t	EC Medium-term outlook report

Source: own processing

Table 1: List of commodities whose price forecasts are assessed (continuation).

<table>
<tr><th></th><th>2009</th><th>2010</th><th>2011</th><th>2012</th><th>2013</th><th>2014</th><th>2015</th><th>2016</th></tr>
<tr><td>AO wheat</td><td colspan="8">A-C</td></tr>
<tr><td>AO corn</td><td colspan="8">A-C</td></tr>
<tr><td>AO butter</td><td></td><td colspan="7">A-C</td></tr>
<tr><td>AO cheese</td><td></td><td colspan="7">A-C</td></tr>
<tr><td>AO EU commodities</td><td></td><td></td><td colspan="6">A-C</td></tr>
<tr><td>EU commodities</td><td></td><td></td><td></td><td></td><td colspan="4">EC A-C</td></tr>
</table>

Note: AO EU commodities — Those of table 1 with name starting with "AO EU" (meats only).
EU commodities — Those of table 1 with name starting with "EU".
A-C — Years in which the AGLINK-COSIMO model was applied.
EC A-C — Years in which the European Commission DG AGRI's version of AGLINK-COSIMO model was applied.

Realized prices as published by the EC (EU commodities) are the same as those published in the OECD-FAO Outlook (AO EU commodities), but forecasts are different between these two Outlooks. AO commodities are also assessed in another setting with different periods (Table 5).

Source: own processing

Table 2: List of commodities and corresponding methods and periods.

were made is in Table 2.

For the evaluation of time series forecasts, there are many possible measures. Hyndman and Koehler (2006) explain why to avoid choosing some of them. They recommend the MASE (Mean Absolute Scaled Error). There is also the Theil's UII (Theil's U2) coefficient (Theil, 1966, as cited in Bliemel, 1973), also referred to as the Relative Root Mean Squared Error (RelRMSE) (De Gooijer and Hyndman, 2006), which is similar to the MASE. The UII penalizes large errors more and when applied on the same forecast it can be either higher or lower, but in the exercise in the present paper both measures lead to very similar results. Since the formula for the UII (Equation 1) is simpler, only results for the UII are presented. It is calculated for each commodity separately.

t… *time (year of the time series of a particular commodity),*

n… *Number of forecasts (of 1 year long horizon) that we evaluate.*

Y_j… *The average realized price over the period: {t;t+1;t+2} where t = j (in the case of OECD and FAO Outlooks) or the realized price at time t (in the case of EC Outlooks).*

$\hat{Y}_j$… *The average of forecasted prices for the period {t;t+1;t+2} where t = j (in the case of OECD and FAO Outlooks) or the forecasted price for time t (in the case of EC Outlooks).*

l… *Number of periods back to the latest time i-l, for which Y_{i-l} is known at the time of predicting Y_i; l = 4 in the case of OECD and FAO Outlooks and l = 2 in the case of EC Outlooks.*

$$UII = \sqrt{\frac{\sum_{t=1}^{n}(\hat{Y}_t - Y_t)^2}{\sum_{t=1}^{n}(Y_t - Y_{t-l})^2}} \qquad (1)$$

Relative errors are scale independent, so they are more easily comparable across commodities. However, each time series is specific not only due to its scale, but also to its length, and variance. The UII might be interpreted as a measure of errors of a sequence of forecasts relative to a corresponding sequence of "naïve" forecasts (the latter is in the denominator of the equation). These "naïve" forecasts predict for time *t* the same price as is the price at time *t - l*. They are comprised of the last whole year available, so *l* is equal to 2 for EU (EC's outlook) prices. But for the AO and AO EU prices, the last available price at time *t* is the average price over *t* - 3, *t* - 2, and *t* - 1.

Davydenko and Fildes (2016) point out an undesirable property of the MASE, which is that it overrates the accuracy of a benchmark forecasting method because of the arithmetic mean used in its formula. However, in the present paper, the UII is applied in such a way that it does not overrate the accuracy of the benchmark forecasting method. For example, if the UII is 0.5, it should be interpreted as the benchmark (naive) forecast having approximately twice as large an error as the nonnaive forecast. This is because 1 (which is the benchmark UII) divided by 0.5 equals 2. On the other hand, if the benchmark is twice as accurate as the nonnaive forecast, the UII is approximately equal to 2. Therefore, for the interpretation of the UII values between 0 and 1 (the UII is never lower than 0): number 1 should be divided by the UII, and the resulting number shows how many times larger error the benchmark has. However, for the interpretation of the UII values greater than 1: without any further computation, the number directly states how many times more accurate the benchmark is. To avoid the undesirable overrating when computing an arithmetic average UII, this paper applies a transformation on the UII if it is lower than 1 (Equation 2):

$$\widetilde{UII} = \begin{cases} UII, & UII \geq 1 \\ 2 - \dfrac{1}{UII}, & UII < 1 \end{cases} \qquad (2)$$

$$AvgUII = Arithmetic\ average(\widetilde{UII}).$$

As Davydenko and Fildes (2016) also note, the arithmetic mean is severely influenced by extreme cases. The transformation in Equation 2 does not prevent this problem. Nevertheless, in the present paper, there are no extreme cases among the selected forecasts.

The UII is a measure which does not provide information on the probability that the assessed forecast is significantly different from the naïve benchmark forecast. Diebold and Mariano (1995) suggests 3 tests to provide such information. The second test (the Sign test) gives at least some idea even if number of observations is very low. The other two tests would be more difficult to compute and interpret. In the present paper, probabilities are presented that the Sign test statistic states its computed value assuming the forecasts are equally accurate. A null hypothesis that they are equally accurate[4] is rejected at the 10% level of significance if the statistic is lower than 0.1.

To discover the nature of the forecast errors, this paper applies an MSE decomposition formula (Cipra, 2013) (Equation 3):

MSE… Mean Squared Error,

σ… *standard deviation,*

ρ… *Pearson's correlation coefficient,*

$$MSE = \sum_{t=1}^{n} \frac{\left(\hat{Y}_t - Y_t\right)^2}{n} = \left(\sum_{t=1}^{n} \frac{\hat{Y}_t}{n} - \sum_{i=1}^{n} \frac{Y_t}{n}\right)^2 + (\sigma_{\hat{Y}} - \sigma_Y)^2 + 2(1 - \rho_{\hat{Y}Y})\sigma_{\hat{Y}}\sigma_Y = MSE_{bias} + MSE_{\sigma} + MSE_{\varepsilon}. \qquad (3)$$

The MSE is also sometimes used for assessing the inaccuracy of forecasts, but here just for the decomposition. The three main parentheses on the right side of Equation 3 divided each by the sum of the three then count to 1 and are called "the bias proportion", "the variance proportion", and "the covariance proportion". The numerator of the bias proportion represents the distance between means of forecast and realised prices, the numerator of the variance proportion represents the difference between the variances of forecast and realized prices, and the numerator of the remaining part indicates a non-systematic error. A forecast can be considered optimal according to this decomposition approach if its covariance proportion (MSEƐ/MSE) is 100 % (the other two proportions are 0 %).

Due to comments by Ahlburg (1984), the authors also apply a decomposition formula called "Theil's decomposition", which is a function of growth indexes rather than absolute values and includes correlation in the second component in addition to the third one (Equation 4):

$$\hat{Y}'_t = \left\{\frac{\hat{Y}_t}{Y_{t-1}}\right\}_{t=1,\dots,n}$$

$$Y'_t = \left\{\frac{Y_t}{Y_{t-1}}\right\}_{t=1,\dots,n}$$

[4] This equality means that the median of differences between these forecasts' absolute errors equals zero.

$$MSE' = \sum_{t=1}^{n} \frac{\left(\hat{Y'}_t - Y'_t\right)^2}{n} = \left(\sum_{t=1}^{n} \frac{\left(\hat{Y'}_t\right)}{n} - \sum_{t=1}^{n} \frac{\left(Y'_t\right)}{n}\right)^2 + \left(\sigma_{\hat{Y'}_t} - \rho_{\hat{Y'}_t Y'_t}\sigma_{Y'_t}\right)^2 + \left(1 - \rho^2_{\hat{Y'}_t Y'_t}\right)\sigma^2_{Y'_t} = MSE'_{bias} + MSE'_{regression} + MSE'_{Theil's\ \varepsilon}. \quad (4)$$

The presence of the correlation coefficient in the second component in Theil's version (Equation 4) often results in higher values of the second component compared to the first version of the decomposition (Equation 3). The three respective components, dividing each by the sum of the three, are called “the bias proportion” (different from “the bias proportion” of Equation 3), “the regression proportion”, and “the disturbance proportion”. The word “regression” recalls the possibility of using a linear regression model for an adjustment of the forecast. This adjustment eradicates the bias and regression proportions of the MSE'. The regression proportion arises from systematic under or over estimation of the slope of the relationship between a realised series and its forecast (Theil, 1971, as cited in Ahlburg, 1984). However, the adjustment is exogenous to the AGLINK-COSIMO model, so it will not be compatible with the model equilibrium.

To avoid misleadings, the two types of decomposition had better not be compared across commodities without accounting for the sum of the three proportions being variable across commodities. This is because the MSE is scale dependent.

To differentiate between the case when forecasts are generally higher than realized prices and the opposite case, the second column in Table 3 signifies whether and how much the sum of forecasts of prices of a commodity is higher or lower than the sum of its realised prices.

To measure how the price forecasts of the OECD and FAO's Agricultural Outlook are consistent, 6 editions are compared, from that published in 2011 to the one published in 2016. Each of these include forecasts of the price of common wheat (in Table 1 the AO wheat) for at least the period 2016-2020[5]. Pairs of outlooks are compared using paired tests on the equivalence of mean values, and the Pearson’s and the Spearman’s correlation coefficients. The Spearman’s correlation coefficient is more robust than the Pearson’s, but requires a transformation of the time series (Huber, 1981).

Results and discussion

For each commodity, the percentage difference between the sum of forecasts and of realisations, the assessment indicator UII, the Sign test probability, and the two versions of the MSE decomposition are calculated from forecasts made within the periods stated in Table 2, and the results are summarized in Table 3.

[5] Therefore, their forecast horizons range from 0 at minimum to 9 years at maximum succeeding the year of publication. The 0 forecast horizon means the projection for the year 2016 published at the same year.

Commodity	$(\sum\hat{Y}_t / \sum Y_t) - 1$	UII	Sign test probability	MSE proportions		MSE' regression proportion of growth indexes
				Bias	Variance	
AO wheat	-8%	1.0	0.273	10%	10%	73%
AO corn	-2%	0.8	0.218	0%	15%	80%
AO EU beef	8%	1.4	0.235	12%	23%	81%
AO EU pigmeat	26%	1.4	0.235	69%	0%	20%
AO EU poultry	7%	0.8	0.093	25%	0%	46%
AO butter	-15%	1.3	0.165	39%	2%	43%
AO cheese	-2%	1.3	0.273	1%	2%	86%
EU wheat	4%	0.2	0.062	61%	1%	0%
EU fbarley	-2%	0.5	0.062	3%	1%	69%
EU maize	-2%	0.2	0.376	12%	1%	2%
EU sugar	17%	0.6	0.250	62%	8%	3%
EU beef	-6%	4.2	0.250	39%	24%	58%

Source: own processing

Table 3: Results by commodity (to be continued).

Commodity	$(\sum\hat{Y}_t / \sum Y_t) - 1$	UII	Sign test probability	MSE proportions		MSE' regression proportion of growth indexes
				Bias	Variance	
EU pigmeat	10%	1.0	0.250	38%	3%	23%
EU poultry	-4%	1.2	0.376	69%	5%	12%
EU milk	-1%	0.5	0.376	1%	54%	23%
EU butter	-8%	0.7	0.250	12%	38%	0%
EU cheese	4%	0.7	0.250	7%	24%	15%

Source: own processing

Table 3: Results by commodity (continuation).

The AO wheat 3-year-average price is forecast much lower in most years of the selected period and the sum of forecasts is 8% lower than the sum of realisations (Table 3). The UII is equal to 1.0, so the A-C forecasts in average have the same errors as the naïve no change forecasts. The sign test probability is not low enough to reject this hypothesis. The regression proportion is high, which means that a more effective forecast could be made using the procedure that Theil suggests.

AO corn 3-year-average price forecasts are more accurate than the naïve no change forecasts, but the hypotheses that the accuracy is the same cannot be rejected. Its MSE decompositions are similar to those of the AO wheat price. In this way, conclusions can be made from Table 3 for each commodity. However, it should be emphasized again that the results can be compared between commodities only if differences between the sample sizes (Table 2) and differences between the total MSEs (Equations 3 and 4 for various *Y*) are taken into account.

Rivera-Ferre & Ortega-Cerdà (2010) use the Mean Absolute Percentage Error measure on the AO published between 1999-2008 for wheat, corn, oilseed, oilseed meal, and rice prices. Corn has the lowest MAPE, 15%, while wheat has 17-18%. In the sample in the present paper (Table 1), corn has 28% and wheat 23% MAPE, so the discrepancy increased with the newer sample. Rivera-Ferre & Ortega-Cerdà also discovered that the MAPE generally increases with the length of the horizon.

Holst (2010) calculates the UII for AO wheat from AO published between 1995-2006, which amounts to 1.0, the same as in the present paper. Interestingly, if the author drops the 2007/2008 observation, which was an extreme, the UII for the 1-year horizon rises to 1.1, although for the other horizons it falls more significantly. There are also two more models in his comparison – the one developed by the Food and Agricultural Policy Research Institute (FAPRI), and one simple autoregressive developed by him specifically for this purpose. The FAPRI has results similar to the OECD-FAO. The AR estimator has similar results in its simplest version, with a potential to improve it by adding some exogenous predictors.

Even though the UII ranges from high to low values, there are only three cases (AO EU poultry, EU wheat, and EU fbarley) where an outlook forecast is significantly better or worse than the naïve no-change forecast (at the 10% level of significance). In all three, the outlook forecast is more accurate, so overall there is no commodity in which the outlook forecast is significantly worse. The highest UII is for EU beef, where most of the error is systematic. Beef price forecasts (both EU and AO EU) have exceptionally bad fits and exceptionally high regression proportions, which suggests using Theil's correction procedure. This procedure might be especially promising with the AO commodities. In general, this should be considered when the percentage difference is simultaneously large, the UII greater than 1, and the regression proportion is high. If the regression proportion is low, but the percentage difference and the bias proportion are large (such as for EU sugar), a simple adjustment for the percentage difference would be more suitable. If the variance proportion is high (EU milk), the analysis of variance can be helpful. If the regression, bias, and variance proportions are all low (EU maize, EU cheese), corrections are less justified.

The second column of Table 3 shows some exceptional patterns. The AO commodities have underestimated prices (minus signs), which could however just be due to evaluating longer periods than for the AO EU commodities, which have overestimated prices. Forecasts made in 2009 and 2010 for AO commodities are exceptionally underestimated, which explains this pattern. On the other hand, EU commodities, having every one the same four-year period of publishing which mostly overlaps those of the AO and AO EU, have forecast prices both higher and lower than they realise.

Table 4 partly repeats the UII results from Table 3 (3-year averages column) and compares them to UIIs computed from 1-year data (the realizations are taken from the http://stats.oecd.org website). AO EU commodities (meats) realisations differ to a great extent between the Outlook publication and the website, so the comparison cannot be made.

The comparison of Table 4 is flawed in that the sample lengths are not the same. Still, it generally gives an example that the second variant lead to slightly better results. This is because the horizon is always shorter than in the first variant. At any rate, the decision to primarily use the 3-year averages instead of the data from the website has not affected the results for AO commodities very much.

To summarize for each commodity, 7 indicators are computed. From all 17 commodities, 9 have prices forecast more accurately than they would have if the specified naïve no change forecast was used instead. As far as the 7 selected commodities from the OECD&FAO's Agricultural Outlook (method A C) are concerned, the mean UII (Equation 2) is 1.1, and there are 2 with higher accuracy compared to the naïve forecast. For the EU's Medium term agricultural outlook (method EC A C), there are 10 selected commodities. Their mean UII is 0.2. 7 are forecast more accurately than using the naïve method. That is much lower than for the OECD&FAO's Agricultural Outlook, partly as a consequence of higher lag l in Equation 1.

These results do not mean that the 8 commodity forecasts that do not outperform the naïve forecasts should be abandoned. They have important qualities that the measures used in the evaluation in this paper do not capture. Firstly, the forecasts are part of a structural model or reasoning which the naïve forecasts cannot match. Secondly, the accuracy of forecasts could be improved by calibration of the forecasting model, which is not possible with the naïve forecasts. Thirdly, the time series used in the analysis in this paper are very short, so there is a high probability that by adding new observations the results will change a bit.

The Theil's correction procedure is only feasible for an external user of the outlooks when realized prices are available for the period of interest. This means for example that in July 2019, it can be applied to correct a forecast of AO and AO EU commodities 2020-22 average prices using the errors of the ex-post-forecasts made in periods described in Table 2. In December 2019, it can be similarly applied to correct a forecast of EU commodities 2020 prices. The periods described in Table 2 are those that the results (Table 3 and 4) and discussion in this paper are based upon, but a selection of different sample periods is possible. The correction procedure can be recalculated on a longer sample when new editions of the outlooks are available.

OECD does not publish its own ex post evaluation of the AGLINK-COSIMO price forecasts, nor does the European Commission. Nevertheless, OECD (2017) refers to a stochastic analysis of the OECD&FAO's Agricultural Outlook. It is based on 1,000 simulations with varying selected macroeconomic and yield parameters, which provide ex ante information about how large the price forecast error will be in 80% of cases. In the example presented, a maize price forecast has an asymmetric distribution – there is higher risk of a large positive than a large negative price movement. Such skewness is characteristic for the other AO and AO EU commodities as well. These results can be useful when operating with the A-C price forecasts.

Table 5 shows that there are significant negative correlation coefficients between the editions. Given that the methodology of the Outlook does not

Commodity	3-year averages		1-year	
	UII	sample length	UII	sample length
AO wheat	1.0	2009-2016	1.0	2006-2016
AO corn	0.8		0.7	2007-2016
AO butter	1.3	2010-2016	1.3	2010-2016
AO cheese	1.3		0.9	

Note: Computation with 1-year data allows for a longer sample
Source: own processing

Table 4: Comparison of 3-year averages with yearly data.

		A (2011)		B (2012)		C (2013)		D (2014)		E (2015)	
		Cor	2-side pr	Cor	2-side pr	Cor	2-side pr	Cor	2-side pr	Cor	2-side pr
B	Pear	0.46	0.43								
	Sprm	0.00	1.00								
C	Pear	0.21	0.73	0.96	***0.01						
	Sprm	-0.40	0.50	0.90	**0.04						
D	Pear	0.36	0.56	0.98	***0.00	0.97	***0.01				
	Sprm	0.10	0.87	0.90	**0.04	0.80	0.10				
E	Pear	0.03	0.96	0.81	*0.09	0.90	**0.04	0.80	0.10		
	Sprm	-0.40	0.50	0.90	**0.04	1.00	***0.00	0.80	0.10		
F	Pear	-0.83	*0.08	-0.10	0.87	0.15	0.81	-0.08	0.90	0.43	0.47
	Sprm	-0.80	0.10	0.30	0.62	0.50	0.39	0.10	0.87	0.50	0.39

Note: The year in parenthesis is the publishing year of the edition. Pear assumes normality, Sprm does not. Normality is not tested due to small number of observations (5 obs.). The null hypothesis is that the correlation coefficient is zero. In the 2-side pr columns, ** means significance at the 5% level (* at 10%, *** at 1%). Rejection is at the 5% level of significance
Source: own processing

Table 5: Correlation coefficients of prices of common wheat from 6 editions of the OECD and FAO's Agricultural Outlook.

basically change, it is interesting to find a change in a projected trend from positive to negative or vice versa. Such a change is especially true for the pair A and F. The coefficients suggest that the break point in the series of editions of the Outlooks happens between E (2015) and F (2016). A change in projection cannot also be rejected between A and B. Otherwise, the dynamics of projections does not change significantly from one edition to the next.

The correlation coefficients prove that the price forecasts really are sensitive on the parameters of the model. It is not clear whether this sensitivity is based on real economic determinants or not. Von Lampe et al. (2014) show that there are many factors that influence the price forecast. The sole existence of various definitions of the representative world price in models other than the AGLINK -COSIMO gives reason to assume some incertitude regarding the outlooks. Out of the 10 global models for agriculture examined in the article, 3 forecast an overall real price for agriculture to be declining until 2030 whereas the others forecast it to be mostly rising. There are also large regional differences according to these models. Using the forecasts in some applications might also require setting some international financial exchange parameters, which each model computes in its own way.

Conclusion

The spectrum of results of evaluation of using the OECD&FAO's and EC DG AGRI's outlooks as forecasts of world and EU prices of agricultural commodities on one year horizon is wide for each of the selected measures. There are no two commodities that can be shown to have the same overall results.

The forecasts may certainly be used as regards the AO EU price of poultry, the EU price of common wheat and feed barley, since it is statistically proven here that they are better than the naïve no-change estimator. For other commodities, the results only help in a decision where many other factors should be taken into account. These factors include the possibility of using the forecasts of another models or estimators, the existence of more possible definitions of the representative prices, or the sensitivity of the forecasts on model parameters. Different models sometimes produce substantially different forecasts.

The sensitivity of price forecasts is especially a problem for periods when there are changes in policy. Forecasting accuracy depends a lot on the choice of the sample period. It also depends on the length of the horizon – for the one-year-ahead forecasts of prices of some commodities (EC outlook beef price), the accuracy is exceptionally low. For longer forecasting horizons, some studies show that their potential is greater. As for the future editions of the OECD-FAO and the EC outlooks, there is a potential for the accuracy to become higher relative to simple time-series estimators due to the enlargement of databases.

Regarding the OECD-FAO's Agricultural Outlook, this paper shows that projections are changing from year to year publication. Usually they are positively correlated, but there are some exceptions where the correlation is significantly negative. That means that projections of some commodities may vary dramatically.

In some cases, the authors recommend considering an adjustment of the outlook forecast on the year after the year of publication. This adjustment could be based on computing forecast errors of forecasts from previous editions of the outlook. If these errors have a systematic pattern, there is a chance to obtain a more accurate forecast for one particular commodity in one particular year. Such forecasts will not be in the original structural relation to other variables of the outlook nor to the following 8 years of the outlook projection.

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World´s 24 Biggest Agricultural Producers` Eco-Efficiency Considering Undesirable Outputs

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Abstract

There is still a lack of studies, which are comparing the eco-efficiency of the world`s biggest agricultural producers, which affect the development of agricultural policy the most, not just EU countries. Therefore, the main goal of this article is to evaluate and compare the eco-efficiency of the world`s 24 biggest agricultural producers in time and space and verifying the hypothesis that all the biggest agriculture producers are eco-efficient. Due to the improvement of technologies, we expect a positive development of agricultural eco-efficiency during the time. Eco-efficiency of the world's 24 biggest agricultural producers is computed for the years 2007 and 2017, using an output-oriented DEA model with two undesirable outputs. Data are obtained from FAOSTAT for the years 2007 and 2017. 15 countries have an eco-effective agricultural sector in both years 2007 and 2017 and could be considered as sustainable efficient countries. On average the agricultural eco-efficiency is decreasing over time. Based on the eco-efficiency values, the biggest agricultural producers are divided into three eco-efficiency agricultural groups – eco-efficiency leaders, eco-efficiency followers, and eco-efficiency laggards. According to the results, the research hypothesis that all the biggest agriculture producers are eco-efficient is not confirmed. Likewise, in general, technology improvement during time does not lead to a positive development of agricultural eco-efficiency.

Keywords

Agricultural eco-efficiency, DEA, undesirable output.

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Introduction

Still, continuous population growth exerts pressure on growing production to ensure food security. According to Sielska and Kuszewski (2016), most agricultural producers have limited possibilities for changing their production. With agricultural producers' effort to produce as much as possible with the given inputs, the efficiency inputs – outputs transformation comes to the fore. Nowadays in a highly competitive environment, efficiency is one of the most frequently applied terms to help identify the evaluated units` strengths and weaknesses (Kočišová, 2015). At the same time important sustainable and environmental goals pushing producers to avoid or reduce as much as possible the environmental consequences of their production. Therefore, the notion of eco-efficiency is becoming an integral part of all scientific, public debate, and government goals. The concept of eco-efficiency can be traced back to the 1970´s as the concept of "environmental efficiency" (Freeman et al., 2014). Already in the 1970´s many companies developed and begun to implement their own environmental performance goals to reach environmental efficiency. Minnesota Mining & Manufacturing CO. (3M), for example, focused on the 3P (pollution prevention pays) program implementation in 1975 aiming to prevent pollution at the source (DeSimone and Popoff, 2000). This concept was firstly proposed by Schaltegger and Sturm (1990) as a "business link to sustainable development".The first definition of this notion was introduced by World Business Council for Sustainable Development (WBCSD) in 1992: "eco-efficiency is achieved by the delivery of competitively priced goods and services, that satisfy human needs and brings them life quality, while progressively reducing ecological impact and resource intensity throughout the life cycle to a level at least consistent with the earth`s estimated carrying capacity" (DeSimone and Popoff, 2000). Later eco-efficiency was officially defined also by OECD (1998) as "the efficiency with which ecological resources are used to meet human needs".

Eco-efficiency in the simplest of terms is about achieving more with less, that means more agricultural outputs, in terms of quantity and quality, for less input of land, water, nutrients, energy, labor, or capital. This concept encompasses both the ecological and economic dimensions of sustainable agriculture (Keating et al., 2010). Eco-efficiency increases when the maintenance or growth of the production economic value corresponds to a decrease in environmental impacts (Kharel and Charmondusit, 2008). Therefore, eco-efficiency represents an important tool for assessing agriculture sustainability and also for developing strategies for policymakers, in terms of resource use and environmental impacts (UNESCAP, 2009).

Eco-efficiency is an effective index for assessing agricultural sustainability on three different levels: on macro-economic (national level), on meso-economic (regional level), and on micro-economic (firm-level). The movement from the firm level to the higher levels is caused by the government's interest in applying eco-efficiency principles because these are considered to results in national long-term advantages in terms of international competitiveness (Hur et al., 2004). Numerous studies with different applied methodologies are focused on the evaluation of environmental impacts that agriculture has on the environment. The most widely used approaches are the ratio approach, the material flow analysis, the sustainable value approach, and the frontier approach (Yang and Zhang, 2018). According to Zhang (2008), the ratio approach defines eco-efficiency as the relationship between the economic value of some goods and their environmental impact, but its limitation is that it can be used only if numerator and denominator can be integrated into a certain value. Mickwitz et al. (2004) and Seppälä et al. (2005) apply a ratio approach to evaluate eco-efficiency in a Finnish region of Kymenlaakso. The material flow analysis approach, especially the Life Cycle Assessment (LCA) methodology is widely used in the literature to assess eco-efficiency with the focus on a potential environmental impact that occurred throughout the whole life cycle of a product (Seppälä et al., 2005; Kicherer et al., 2007; Baum and Bienkowski, 2020). However, this approach requires large amounts of hard-to-find data with consequent approximations (Yang and Zhang, 2018). The sustainable value approach is used to analyze eco-efficiency from a wider perspective to evaluate not just the eco-efficiency but at the same time also sustainability (Figge and Hahn, 2003; Grzelak et al., 2019). The sustainable value-added takes into account both, the efficiency and the absolute level (effectiveness) of resource use. Sustainable value-added is an extra value created when the overall level of environmental and social impacts is kept constant, and it considers simultaneously economic, environmental, and social aspects (Figge and Hahn, 2003). From all approaches mentioned above, the most common is a frontier approach, divided into parametric (Stochastic frontier analysis) and non-parametric (Data envelopment analysis). Stochastic frontier analysis (SFA) is applied to measure eco-efficiency on all possible levels – on firm-level (Orea and Wall, 2016), on a regional level (Deng and Gibson, 2019), and on a national level (Robaina-Alves et al., 2015; Shahabinejad et al., 2012). This approach permits an analysis of the potential substitutability between environmental pressures, and can easily be extended to incorporate determinants of eco-efficiency (Orea and Wall, 2016). The disadvantage of the parametric approach is that the output side can not be represented by more than one output variable, and therefore it is difficult to distinguish between desirable and undesirable variables. Data Envelopment Analysis (DEA) demonstrates great potential in the eco-efficiency measurement. DEA measures efficiency using linear programming and it is a useful methodology for aggregating different environmental impacts to construct a comprehensive eco-efficiency indicator because DEA does not require explicit weights, and can avoid the problem related to weighting in LCA (Dyckhoff and Allen, 2001). In a comparison with SFA, DEA allows us to use several output variables and take into account also the environmental consequences of production as undesirable outputs.

Several studies are applying DEA methods to analyze agricultural eco-efficiency at the firm level (Iribarren et al., 2011; Picazo-Tadeo et al., 2011; Gómez-Limón et al., 2012; Beltra´n-Esteve et al., 2014; Urdiales et al.,2016; Bonfiglio et al., 2017, Godoy-Durán et al., 2017). Different types of DEA models as CCR model (Charnes, Cooper and Rhodes), BBC model (Banker, Charnes and Cooper), FDH model (Free Disposal Hull), Super-efficiency model (SEDEA), Slack-based model (SBM), Super SBM model together with other methodological approaches are used to measure regional agricultural eco-efficiency in China (Liu et al., 2020; Pang et al., 2016; Yang et al., 2014) and chosen European countries - Spain (Galdeano – Gómez et al., 2017), Italy (Coluccia et al., 2020), and Poland (Masternak-Janus and Rybaczewska-Blazejowska, 2016). The similar non-parametric methods - DEA techniques are applied to evaluate the eco-efficiency performance of agriculture production at the macro-level (Kočišová, 2015; Blazejowka and Gierulski, 2018; Grovermann et al., 2019). At the national and regional level researchers have developed a variety of DEA efficiency models considering undesirable outputs, representing the agricultural production outputs, which have a bad influence on the environment (Song et al., 2012; Piao et al., 2019; Fandel and Bartova, 2018).

There is still a lack of studies, which are comparing the eco-efficiency of the world`s biggest agricultural producers, which affect the development of agricultural policy the most, not just EU countries. Therefore, the main goal of this article is to evaluate and compare the eco-efficiency of the world`s 24 biggest agricultural producers in time and space and verifying the hypothesis that all the biggest agriculture producers are eco-efficient. Due to the improvement of technologies, we expect a positive development of agricultural eco-efficiency during the time.

Material and methods

4 input variables, namely employment in agriculture (Employment), represented by persons employed in agriculture per 1000 inhabitants, pesticides used in agriculture (Pesticide) in tones/1000 persons, fertilizers used in agriculture (Fertilizers) in tones/1000 persons, and capital consumed in agriculture (CapConsump) in dollars/person and 3 output variables, namely agricultural production (Production) in dollars/person, CH_4 emissions produced in agriculture (CH4emis) in gigagrams/100000 persons and NO_2 emissions produced in agriculture (NO2emis) in gigagrams/100000 persons are selected for estimation of eco-efficiency. Agricultural production represents desirable output; CH_4 emissions and NO_2 emissions represent the undesirable outputs of agricultural production. The selection of variables is in line with research goals. Input and output variables are chosen to cover both the economic and environmental sides of agricultural production (Song et al., 2012; Piao et al., 2019; Fandel and Bartova, 2018). Data are obtained from FAOSTAT for the years 2007 and 2017. According to the agricultural production output value, 24 countries with the worldwide highest agricultural output are selected, namely Argentina (AR), Australia (AU), Canada (CA), Colombia (CO), Egypt (EG), France (FR), Germany (DE), Indonesia (ID), Iran (IR), Italy (IT), Japan (JP), Malaysia (MY), Mexico (MX), Pakistan (PK), Philippines (PH), Korea (KR), Russia (RU), Saudi Arabia (SA), Spain (ES), Thailand (TH), Turkey (TR), United Kingdom (GB), United States (US), Vietnam (VN).

Descriptive statistics as mean, median, standard deviation, maximum, and minimum are computed to make a multidimensional comparison of the selected countries (Yang et al., 2015; Piao et al., 2019; Coluccia et al., 2020)

Data envelopment analysis (DEA), which is a nonparametric frontier methodology, first introduced by Charnes, Cooper, and Rhodes (1978), is used to estimate the agricultural eco-efficiency of the world`s biggest agricultural producers. Data envelopment analysis uses linear programming to evaluate the relative efficiencies or inefficiencies of decision-making units (DMUs) which produce multiple outputs using multiple inputs. DMUs are represented by the 24 biggest agricultural producers in the world. The DEA methodology demonstrates great potential in the eco-efficiency evaluation because no explicit weights are needed to aggregate efficiency indicators (Dyckhoff and Allen, 2001). Suppose we have n independent homogeneous decision-making units, denoted by DMU_j (j = 1, 2, …, n). For given p non-discretionary inputs $Z_j = (z_{1j}, z_{2j}, \ldots, z_{pj})^T$, each DMU consumes m discretionary inputs $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ to produce s outputs $Y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$ (Hua, Bian, and Liang, 2007). Standard linear output-oriented CCR model with a constant return to scale could be written as following linear programming problem:

$$\begin{gathered} \boldsymbol{Max\ \theta_q} \\ \sum_{j=1}^{n} \boldsymbol{y_{rj}\lambda_j \geq \theta Y_{rq}} \qquad \boldsymbol{r = 1, \ldots s} \\ \sum_{j=1}^{n} \boldsymbol{x_{ij}\lambda_j \leq X_{iq}} \qquad \boldsymbol{i = 1, \ldots m} \\ \boldsymbol{\lambda_j \geq 0} \qquad \boldsymbol{j = 1, \ldots n} \end{gathered} \qquad \text{(Model 1)}$$

Where Θ_q represents the technical efficiency of the DMU_q and λ_j represents the weight assigned to the DMU_j (j = 1, 2, …, n).

During the production process under normal circumstances, undesirable outputs like environmental pollutants will be inevitably produced, therefore, undesirable outputs must be also taken into account in an eco-efficiency evaluation. Because we like to produce desirable outputs as much as possible and at the same time the undesirable outputs as little as possible for a given level of inputs, it is necessary to transform undesirable outputs first and then it is possible to evaluate eco-efficiency by using the traditional efficiency model based on the transformed data (Song et al., 2012).

First, each undesirable output should be multiplied by "-1" and then a proper translation vector *w* should be found to let all negative undesirable outputs be positive (Seiford and Zhu, 2002).

$$y_j^{-b} = -y_j^b + w > 0 \qquad (1)$$

$$y_j^{-b} = -y_j^b + max_j(y_j^b) + 1 \qquad (2)$$

After undesirable output translation, output-oriented DEA model could be written as following linear programming problem:

$$Max\ \theta_q$$

$$\sum_{j=1}^{n} y_{rj}^{g}\lambda_j \geq \theta Y_{rq}^{g} \qquad r \in G\ (desirable)$$

$$\sum_{j=1}^{n} y_{tj}^{-b}\lambda_j \geq \theta Y_{tq}^{-b} \qquad t \in B\ (undesirable) \qquad \text{(Model 2)}$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq X_{iq} \qquad i = 1, \dots m$$

$$\lambda_j \geq 0 \qquad j = 1, \dots n$$

Results and discussion

Agricultural eco-efficiency inputs and outputs variables of the chosen 24 biggest agricultural producers are analyzed in the first part of the article. Basic descriptive statistics are computed for two years -2007 and 2017 (Table 1).

The average number of persons employed in agriculture per 1000 inhabitants is decreasing from 63.76 in 2007 (Employment07 in Table 1) to 53.71 persons/1000 inhabitants in 2017 (Employment17 in Table 1). The variability of this variable is decreasing during the time (+-59.23 persons/1000 inhabitants in 2017, +-70.48 persons/1000 inhabitants in 2007). In both analyzed years, the median is lower than mean, which indicates that more than half of the analyzed countries have lower employment in agriculture than is the average value. The highest employment in agriculture is in both years recorded in Vietnam (227.96 persons/1000 inhabitants in 2017 and 265.45 persons/1000 inhabitants in 2007), the lowest in Argentina (0.16 persons/1000 inhabitants in 2017 and 3.14 persons/1000 inhabitants in 2007).

Variable	Units	MEAN	MEDIAN	STDEV	MAX value	MAX Country	MIN value	MIN Country
Employment17	persons/1000 inhabitants	53.71	27.57	59.23	227.96	Vietnam	0.16	Argentina
Employment07	persons/1000 inhabitants	63.76	39.41	70.48	265.45	Vietnam	3.14	Argentina
Pesticide17	tones/1000 persons	0.80	0.46	1.04	4.46	Argentina	0.00001	Philippines
Pesticide07	tones/1000 persons	0.81	0.49	0.99	4.68	Argentina	0.01	Indonesia
Fertilizers17	tones/1000 persons	31.90	24.13	24.70	106.75	Canada	8.08	Japan
Fertilizers07	tones/1000 persons	34.54	24.97	24.99	98.79	Australia	9.43	Philippines
CapConsump17	dollars/person	99.18	84.98	90.08	398.07	Australia	0.84	Egypt
CapConsump07	dollars/person	93.30	60.78	101.18	420.02	Australia	6.07	Mexico
Production17	dollars/person	635.94	568.18	289.57	1342.84	Australia	240.07	Mexico
Production07	dollars/person	626.08	532.83	334.42	1339.94	Australia	170.60	Mexico
CH4emis17	gigagrams/100000 persons	2.47	1.76	2.99	14.65	Australia	0.34	Saudi Arabia
CH4emis07	gigagrams/100000 persons	2.85	1.92	3.73	18.24	Australia	0.40	Saudi Arabia
NO2emis17	gigagrams/100000 persons	0.15	0.10	0.20	0.99	Australia	0.02	Japan
NO2emis07	gigagrams/100000 persons	0.16	0.10	0.23	1.15	Australia	0.02	Japan

Source: FAOSTAT, own calculations

Table 1: Descriptive statistics for years 2007 and 2017.

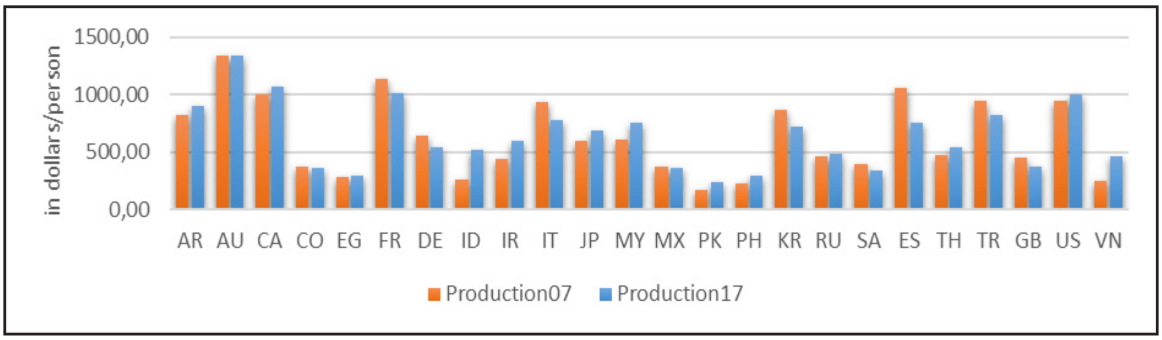
The average amount of pesticides used in agriculture is decreasing from 0.81 tones/1000 persons in 2007 (Pesticide07 in Table 1) to 0.80 tones/1000 persons in 2017 (Pesticide17 in Table 1). The variability of used pesticides, represented by standard deviation, is growing from 0.99 tones/1000 persons in the year 2007 to1.04 tones/1000 persons in the year 2017. In both years the median value of this variable is markedly lower than the average, so more than 50% of analyzed countries use a lower amount of pesticides than is an average value. In both years Argentina is a country with the highest amount of pesticides used in agriculture (4.68 tones/1000 persons in 2007 and 4.46 tones/1000 persons in the year 2017). In 2007 the minimum value of pesticide used is achieving by Indonesia (0.01 tones/1000 persons), in 2017 by the Philippines (0.00001 tones/1000 persons).

The average amount of fertilizers used in agriculture is decreasing from 34.54 tones/1000 persons in 2007 (Fertilizers07 in Table 1) to 31.90 tones/1000 persons in 2017 (Fertilizers17 in Table 1). The variability of fertilizers used is decreasing from 24.99 tones/1000 persons in 2007 to 24.70 tones/1000 persons in 2017. Median of fertilizers used is also decreasing from 24.97 tones/1000 persons in 2007 to 24.13 tones/1000 persons in 2017, in both years is lower than mean. In the year 2007, the minimum amount of fertilizers is used in the Philippines (9.43 tones/1000 persons), the maximum in Australia (98.78 tones/1000 persons). In the year 2017 the minimum amount of fertilizers is used in Japan (8.08 tones/1000 persons), the maximum in Canada (106.75 tones/1000 persons).

The average value of the capital consumed in agriculture is growing from 93.30 dollars/person in 2007 (CapConsump07 in Table 1) to 99.18 dollars/person in 2017 (CapConsump17 in Table 1). In both analyzed years median is lower than mean, so more than 50 % of selected countries use less capital in agriculture than average. Variability of capital consumption is decreasing from 101.18 dollars/person in 2007 to 90.08 dollars/person in 2017. The highest capital consumption in agriculture is in both years recorded in Australia (398.07 dollars/person in 2017 and 420.02 dollars/person in 2007). The lowest capital consumption in agriculture is recorded in 2017 in Egypt (0.84 dollars/person) and in 2007 in Mexico (6.07 dollars/person).

The average agricultural production is growing from 626.08 dollars/person in 2007 (Production07 in Table 1) to 635.94 dollars/person in 2017 (Production17 in Table 1). At the same time, the variability of agricultural production is decreasing from 334.42 dollars/person in 2007 to 289.57 dollars/person in 2017, which means, that the differences between 24 analyzed countries are decreasing. In both analyzed years the median of agricultural production is lower than its mean, which indicates that more than 50% of selected 24 countries produce less than the average value. The biggest agricultural producer in dollars/person in both years is Australia with 1339.94 dollars/person in 2007 and 1342.84 in 2017. The lowest agricultural producer in dollars/person in both years is Mexico with 170.60 dollars/person in 2007 and 240.07 dollars/person in 2017.

The agricultural production of some selected countries grows during the analyzed time. Argentina (AR), Australia (AU), Canada (CA), Egypt (EG), Indonesia (ID), Iran (IR), Japan (JP), Malaysia (MY), Pakistan (PK), Philippines (PH), Russia (RU), Thailand (TH), United States (US) and Vietnam (VN) have higher agricultural production in 2017 than in 2007. On the other hand, agricultural production of Colombia (CO), France (FR), Germany (DE), Italy (IT), Mexico (MX), Korea (KR), Saudi Arabia (SA), Spain (ES), Turkey(TR) and United Kingdom (GB) decreases during analyzed years 2007 and 2017 (Figure 1).



Source: FAOSTAT, own calculations

Figure 1: Agricultural production of selected 24 biggest world agricultural producers in 2007 and 2017.

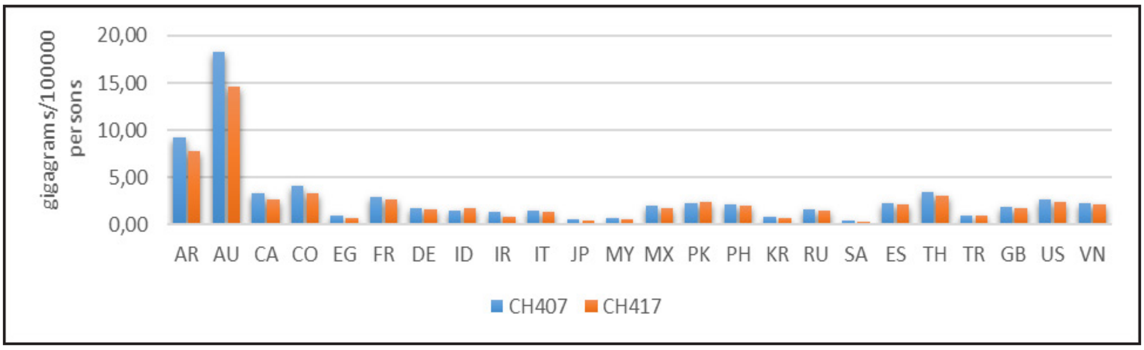
The average value of CH_4 emissions produced in agriculture is decreasing during the time from 2.85 gigagrams/100000 persons in 2007 (CH4emis07 in Table 1) to 2.47 gigagrams/100000 persons in 2017 (CH4emis17 in Table 1). Variability of CH_4 emissions, expressed by standard deviation, is also decreasing during the time. In both years 2007, 2017 median of CH_4 emissions is smaller than mean, which indicates that more than 50% of selected countries produce less CH_4 emissions from agriculture than is average for all countries. In both years Australia, which ratified the Kyoto protocol about green gas emission reduction later than other countries, produces the highest amount of CH_4 emissions (18.24 gigagrams/100000 persons in 2007 and 14.65 gigagrams/100000 persons in 2017). Saudi Arabia produces the smallest amount of CH_4 emissions (0.40 gigagrams/100000 persons in 2007 and 0.34 gigagrams/100000 persons in 2017).

The agricultural CH_4 emissions production of almost all selected countries decreases in the year 2017 in a comparison with the year 2007 (Figure 2). The only exceptions are Indonesia (ID), Pakistan (PK), and Turkey (TR), which produce more CH_4 emissions in the year 2017 than before in the year 2007.

The average value of NO_2 emissions produced in agriculture is decreasing during the time from 0.16 gigagrams/100000 persons in 2007 (NO2emis07 in Table 1) to 0.15 gigagrams/100000 persons in 2017 (NO2emis17 in Table 1). The variability of this indicator is also decreasing. In both years 2007, 2017 median of CH_4 emissions is smaller than its average value, which means that more than 50% of selected countries produce less NO_2 emissions from agriculture than on average. Again in both years, Australia is the biggest agricultural producer of NO2 emissions (1.15 gigagrams/100000 persons in 2007 and 0.99 gigagrams/100000 persons in 2017), and Japan is the lowest agricultural NO2 emission producer (0.02 gigagrams/100000 persons in 2007 and 2017).

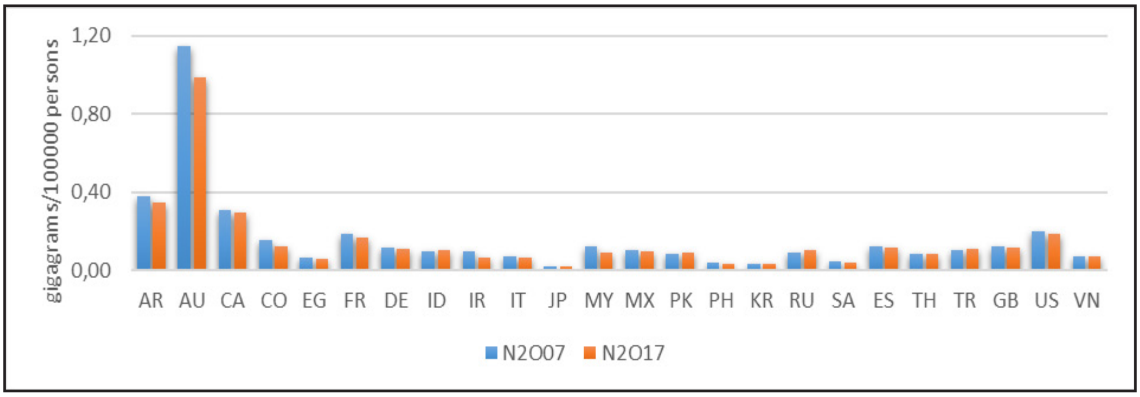
Agricultural NO_2 emissions production development in the selected countries is the same as the development of agricultural CH_4 emissions production, the production is growing only in the case of Indonesia (ID), Pakistan (PK), and Turkey (TR). Other countries produce less NO_2 emissions in 2017 than in 2007 (Figure 3).

In regards to environmental issues, every agricultural producer should pay attention



Source: FAOSTAT, own calculations

Figure 2: Agricultural CH_4 emissions production of selected 24 biggest world agricultural producers in 2007 and 2017.



Source: FAOSTAT, own calculations

Figure 3: Agricultural NO_2 emissions production of selected 24 biggest world agricultural producers in 2007 and 2017.

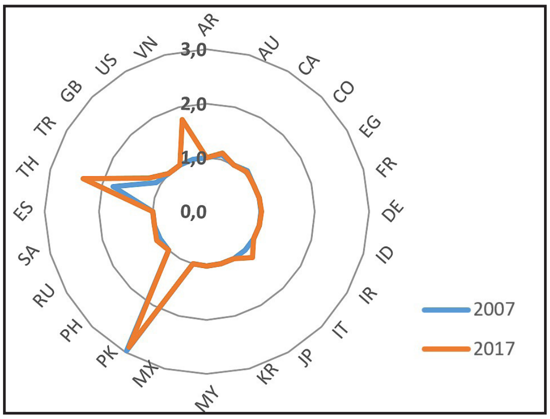
to the eco-efficiency of transforming inputs into outputs. Only if the agriculture producer is eco-efficient, can produce as much agricultural output as possible with given inputs and at the same time take into account the environmental impact of its production.

Eco-efficiency of the world's 24 biggest agricultural producers is computed for the years 2007 and 2017, using an output-oriented DEA model. 2 agricultural and 2 environmental variables stand on the inputs site, namely employment in agriculture, agricultural capital consumption, pesticides use and fertilizers use. 1 agricultural and 2 environmental variables stand on the outputs side – agricultural production, CH_4 emissions production, N_2O emissions production. In an output -oriented model, technical efficiency can take on a value equal to 1 and higher, whereas if the country effectively transforms inputs on outputs, reaches technical efficiency (TE) equals 1. Computed TE higher than 1 means, that from given inputs could the country produce more outputs if it will be efficient.

The agricultural eco-efficiency of selected 24 biggest world agricultural producers is presented in Figure 4. 15 countries have an eco-effective agricultural sector in both years 2007 and 2017, namely Argentina (AR), Canada (CA), Egypt (EG), France (FR), Indonesia (ID), Iran (IR), Japan (JP), Korea (KR), Malaysia (MY), Mexico (MX), Philippines (PH), Saudi Arabia (SA), Spain (ES), United Kingdom (GB) and United States (US). Those 15 countries - 63% of selected countries could be considered as sustainable efficient countries. Compare to the Sielska and Kuszewski (2016) research`s results still more and more countries can keep their eco-efficiency during the time, from 1996 to 2011 only 41% of FADN regions retained their eco-efficiency but based on our results from 2007 to 2017 63% of analyzed countries retained their eco-efficiency. Germany (DE), Italy (IT), Russia (RU), and Vietnam (VN) are eco-effective in 2007, but not anymore in 2017. In 2017 they have TE values higher than 1. The cause of their eco-efficiency worsening is that with their given inputs they produce less agriculture output or higher emissions as are optimal. Germany over time increases some of its inputs and despite that at the same time decreases its production value. Italy over time decreases all of its inputs and therefore at the same time decreases also production value and emissions, but not in an adequate proportion. Russia increases almost all inputs and therefore also production value, which is accompanied by a higher value of undesirable output - N_2O emission production. Vietnam over time increases almost all inputs, and therefore also production value, but again also both undesirable output – emissions.

The agricultural sector in Germany is also not eco-efficient according to Blazejowka and Gierulski (2018) and Akande (2012). The different results are found out in the case of Italy, where Blazejowka and Gierulski (2018) claim that the Italian agricultural sector is eco-efficient, and in the case of France, Spain, and the United Kingdom, which they consider being an eco-inefficient. Different research conclusions could be caused by different variable selection. Pokrivčák et al. (2015) argue that Italy, France, and Spain are efficient when we are taking into account only agriculture variables, which indicates that the inefficiency of Italy is caused by environmental indicators.

In both analyzed years Australia (AU), Colombia (CO), Pakistan (PK), Thailand (TH), and Turkey (TR) reach the TE values higher than 1, so they are countries with continuously eco-ineffective agricultural sectors. From eco-ineffective countries Colombia (CO) and Pakistan (PK) get to improve their efficiency during the time, on the other hand, Australia (AU), Thailand (TH), and Turkey (TR) get even worse during the time (Figure 4). Colombia improves eco-efficiency over time because it increases its inputs and at the same time increases also production and decreases emissions. Pakistan increases over time both production and also emissions, but not to the extent of production increase, and therefore also improves its eco-efficiency. Thailand, Turkey, and Australia worsening their eco-efficiency, because they increase the production of at least one type of analyzed emissions over time.



Source: FAOSTAT, own calculations

Figure 4: Agricultural eco-efficiency of selected 24 biggest world agricultural producers in 2007 and 2017.

According to the eco-efficiency values, the biggest agricultural producers are divided into three eco-efficiency agricultural groups (Blazejowka and Gierulski, 2018):

1. **eco-efficiency leaders** (marked by green color in Figure 5) with TE equal to 1,
2. **eco-efficiency followers** (marked by purple color on Figure 5) with TE in an interval (1, 2>,
3. **eco-efficiency laggards** (marked by the red color in Figure 5) with TE higher than 2

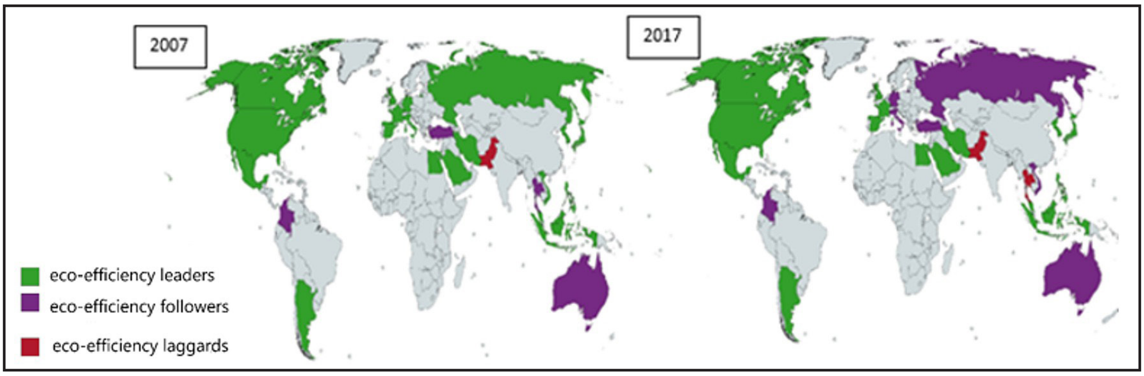
In 2007 19 countries (79% of chosen countries) belong to the group **eco-efficiency leaders**: Argentina (AR), Canada (CA), Egypt (EG), France (FR), Indonesia (ID), Iran (IR), Japan (JP), Korea (KR), Malaysia (MY), Mexico (MX), Philippines (PH), Saudi Arabia (SA), Spain (ES), United Kingdom (GB), United States (US), Germany (DE), Italy (IT), Russia (RU), and Vietnam (VN). Australia (AU), Colombia (CO), Thailand (TH), and Turkey (TR) belong to the group **eco-efficiency followers** and just Pakistan (PK) belongs to the group **eco-efficiency laggards** with eco-efficiency higher than 2. Pakistan should improve its output variables by more than 100% (with given inputs gets higher agricultural output with fewer emissions) when wants to reach an eco-efficient agricultural sector.

On average in 2017 eco-efficiency of 24 world`s biggest agricultural producers gets worst, despite the fact, that environmental protection is increasingly required. In 2017 Germany (DE), Italy (IT), Russia (RU), and Vietnam (VT), which in 2007 belongwed to the group **eco-efficiency leaders**, reach higher TE than 1 and become a part of **eco-efficiency followers** together with Australia (AU), Colombia (CO) and Turkey (TR). So in 2017 to the first group **eco-efficiency leaders** belong 15 countries (63% of chosen countries): Argentina (AR), Canada (CA), Egypt (EG), France (FR), Indonesia (ID), Iran (IR), Japan (JP), Korea (KR), Malaysia (MY), Mexico (MX), Philippines (PH), Saudi Arabia (SA), Spain (ES), United Kingdom (GB) and United States (US). Thailand (TH), which in 2007 belongs to the group **eco-efficiency followers**, in 2017 reaches TE higher than 2 and together with Pakistan (PK) belongs into the group **eco-efficiency laggards** (Figure 5).

63% of analyzed 24 biggest agricultural producers have an eco-efficient agricultural sector in both years, which means that with their inputs they produce as much of agricultural output as possible and at the same time as least of emissions as possible.

On average the agricultural eco-efficiency is decreasing over time. Countries as Germany, Italy, Russia, and Vietnam have a problem retaining their agricultural sector eco-efficient and with their given inputs they start to produce less agricultural output or higher emissions as are optimal.

According to the results, the research hypothesis that all the biggest agriculture producers are eco-efficient is not confirmed. Likewise, in general, technology improvement during time does not lead to a positive development of agricultural eco-efficiency.



Source: FAOSTAT, own calculations

Figure 5: Groups of countries according to their eco-efficiency in 2007 and 2017.

Conclusion

Nowadays agricultural production plays an important role in ensuring food security, due to continuous population growth. On average the 24 selected countries` agricultural production is growing over the years, but the production of 10 selected countries (Colombia, France, Germany, Italy, Mexico, Korea, Saudi Arabia, Spain, Turkey, and the United Kingdom) is decreasing during analyzed years 2007 and 2017. Only in the case that agricultural producers effectively transform their inputs on outputs, they can produce as much as possible with given inputs. During the production process in agriculture under normal circumstances, undesirable outputs like environmental pollutants will be inevitably produced. With today's pressure on the environment improvement the goal of producers is the maximization of their production output and at the same time the minimization of their impact on the environment. But it is very difficult to find a balance between those two areas. The average value of both chosen environmental output variables (CH_4 emissions, NO_2 emissions) for 24 selected countries is decreasing over time (the only countries with growing emissions production during analyzed years are Indonesia, Pakistan, Turkey, and Russia only with growing NO_2 value). According to the computed eco-efficiency, there are 19 countries with an eco-efficient agricultural sector in 2007 (Argentina, Canada, Egypt, France, Indonesia, Iran, Japan, Korea, Malaysia, Mexico, Philippines, Saudi Arabia, Spain, United Kingdom, United States, Germany, Italy, Russia, and Vietnam). In 2017 64% of selected countries (15 countries) are retained their agricultural eco-efficiency compared with 2007 and could be considered as sustainable eco-efficient countries. Germany, Italy, Russia, and Vietnam are not eco-efficient, together with Colombia, Pakistan, Thailand, Turkey, and Australia. Those countries have eco-inefficient agricultural sectors, which consume too many natural resources, use too many fertilizers, and produce a considerable amount of emissions concerning the current level of agricultural production, for example, Australia is a country with the highest value of agricultural production per person, but also with the highest capital consumption, CH_4 and NO_2 emission production. Based on computed results, the given hypothesis "all the biggest agriculture producers are eco-efficient" is not confirmed. According to the eco-efficiency values the biggest agricultural producers are divided into eco-efficiency leaders (with TE=1), eco-efficiency followers (with TE from interval (1, 2>), and eco-efficiency laggards (with TE >2). In 2007, all eco-efficient countries belong to the eco-efficiency leaders. Australia, Colombia, Thailand, and Turkey are eco-efficiency followers and Pakistan is an eco-efficiency laggard. In a comparison with 2007, in 2017 4 eco-efficiency leaders become eco-efficiency followers (Germany, Italy, Russia, Vietnam) and Thailand becomes an eco-efficiency laggard. When we compare the agricultural eco-efficiency changes during the years 2007 and 2017, we can conclude that on average the agricultural eco-efficiency is decreasing over time, and in general technology improvement during the time does not lead to a positive development of agricultural eco-efficiency. Finally, the results of the applied output-oriented DEA method show if the agriculture sector of chosen countries are eco-effective, or not, but it is necessary to investigate deeply the reasons for countries` inefficiency. Future research, based on the findings obtained in this study, can unfold by using the combination of several methodological approaches, as the combination of The Slacks-Based Measure (SBM) of efficiency, Malmquist productivity index, and Tobit model.

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An Analysis of Technical Efficiency of Vegetables' Household Production in Mongolia

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Abstract

Vegetable production is one important agricultural product in crop production after wheat and potatoes production in Mongolia. Currently, household production dominates in total vegetable production (approximately 80 percent). Thus, the purposes of this paper were to measure technical efficiency and to determine influencing factors inefficiency on vegetable household production in Mongolia by using Stochastic production frontier analysis (SFA). Primary data was collected from randomly selected 260 vegetable households of Mongolia in 2019. The empirical result indicated that the average technical efficiency of the sampled vegetable household was 64.6 % (range between 43.2% and 99.9%) or they lost about 35.4% of the potential output due to technical inefficiency. We found that land and labor are the main influencing input factors of the household's vegetable production. Also, the result of the technical inefficiency model, variables of age, sex, experience, and credit use obtained a negative relationship with inefficiency. The other variables are family size, education level, land fragmentation index was positively affected by technical inefficiency.

Keywords

Vegetable production, technical efficiency, stochastic frontier analysis, determinants of technical inefficiency.

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Introduction

Agriculture is a traditional sector of Mongolia and it is still a dominant role in its economy. It contributed to 10.9 % of GDP and employed 25.6 % of the total workforce in 2019 (National Statistics office of Mongolia, 2019). Also, it has been providing food for the population and raw materials for manufacturing industries. The agriculture sector is divided into livestock and crop production. The livestock sector accounts for approximately 89 % of agricultural production, while the remaining 11 % accounts from the crop sector (National Statistics Office of Mongolia, 2018). Although crop production contributed a small share of the agriculture sector, it has been the main condition to supply the population with safety and quality food. Mongolia has a vast land area but arable land is only 0.4 % of total land. For example, in 2019, the total sown area was 526.1 thousand hectares (0.3 % of the total land) that were accounted 65.3 percent for wheat, barley, rye and oats, 2.8 % for potato, 1.6 % for vegetables and the remaining area for fodder crops, technical crops and medical crops (National Statistics Office of Mongolia, 2019).

Since 1959, the crop sector started to develop in Mongolia. In 1989, a total of arable land was 1.38 a million hectares, which was the peak point for the crop sector. After shifted to political and economic transition in 1990, the total sown area had been dropped to 189.5 thousand hectares until 2005. Mongolian Government started to pay attention to this situation and implemented the 3rd Land Rehabilitation Programme between 2008 and 2010. As a result, the total sown area increased to a fully supplied level for wheat, potato demand, and approximately 50 % supplied for vegetable demand. Since 2016, the Mongolian government has started to implement some national subprograms namely, "Mongolian vegetable" and "Mongolian fruit" to increasing domestic production of vegetables and fruit (Ministry of food and Agriculture, 2017).

The national average monthly vegetable consumption was very low level which is expressed that 6 times and 3.5 times below from daily intake by recommended World Health Organization (WHO) and the Ministry of the Health of Mongolia (former name) respectively. Therefore, Mongolia has one of the highest incidences of cardiovascular disease (rank was #14 in the world), which is also the country's leading cause of death. One of the main reasons is lower fruit and vegetable consumption to increase the risk of noncommunicable diseases. It is evidenced that Mongolian people do not use to not too many vegetables every daily diet. For example, according to statistics, 2019, national average monthly vegetable consumption was only 2.1 kg (National Statistics Office of Mongolia, 2019).

In Mongolia, there are planting a few varieties of vegetables due to the climatic extreme condition such as cabbage, carrots, turnips, onions, garlic, cucumber, tomatoes, watermelon, and a small number of peppers, beet, etc. In 2018, total vegetable production was 100.7 thousand tons, the Central and Western regions constituted 81.3% of its and while the remaining 18.7% accounted East, Khangai and Ulaanbaatar regions. Therefore, Selenge, Darkhan-Uul, Tuv (Central region), and Khovd (Western region) are four main growing areas of vegetable production composition with a share of 34.4%, 15.9%, 11.6%, and 11.4%, respectively (National Statistics Office of Mongolia, 2018). Also, the households' production dominates in vegetable production (approximately 80% of total vegetable production).

In recent years, there were implemented many projects to increase vegetable domestic production and possible to supply domestic consumption. For example, "Mongol potato" (2004) and "Inclusive and sustainable vegetable production and marketing" (2016) projects by Swiss Development Cooperation (SDC) (SDC, 2015), "Vegetable value chain program in Mongolia" project by (USAID, 2014), "Current situation analysis of vegetable value chain in Mongolia" (2016) SECiM project by FAO and European Union (SECim, 2016), "Community vegetable farming for livelihood improvement" (2017) project by Japan Fund (Japan Fund for Poverty Reduction, 2017), etc. All the projects focused on how to improve vegetable market situation especially, vegetable value chain mapping (sales, transportation), how to increase household revenue, and to determine faced challenges to household vegetable production. Such as, according to SDC report, the vegetable sector has a lot of challenges, for instance, there is a lot of old sorts of vegetable, lack of machinery, equipment and warehouse, profession and technical advice is not enough, households' cooperative is low, lack of market information and lack of correspondence between household and public sector (SDC, 2015). Therefore, as a result of the SDC project, there has improved seed production of vegetables, brought about a more convenient market for vegetables, and increased household production. Productivity is a very important economic factror in international trade and investment (Makieła, Wojciechowski and Wach, 2021). However, agricultural productivity and efficiency studies (including Bayarsaihan and Coelli (2003); Bhattarai (2019)) still seem to be rare but, there is no efficiency analysis of household-level vegetable production. Many policymakers need to focused on improving productivity and efficiency as an important source of potential growth in vegetable production. Therefore, the objectives of this study are to measure technical efficiency and to determine influencing factors inefficiency on vegetable households level in Mongolia.

Materials and methods

Literature review

Efficiency is one of the most important concepts in production. Specifically, technical efficiency is expressed as the side of production and defined as the level of production that ratio between the observed output to the potential output (Coelli, Battese, 2005; Kocisova et al., 2018). Most of the technical efficiency analysis mainly focused on farm-level efficiency and socio-economic characteristics affecting technical inefficiency and efficiency level. (Nyemeck et al., 2008; Galnaitytė et al., 2017) the study provided technical efficiency of groundnut and maize-based systems farmers in the slash and burn agriculture zone of Cameroon, and to identify farm-specific characteristics that explain the variation inefficiency of individual farmers. An understanding of these relationships could provide the policymakers with information to design programs that can contribute to measures needed to expand the food production potential of the nation. Also, they representing socio-economic characteristics of the farm to explain inefficiency, including education (number of completed years of schooling for the farmer), age (number of years of the farmer), distance of the plot from the main access road (kilometers), soil fertility index, club (a dummy variable to measure if the farmer is a member to a peasant club or association), extension contact (dummy variable to measure the influence of agricultural extension on efficiency) and access to cash credit (dummy variable to measure the influence of credit access on efficiency). The study results show that the distance of the plot from the main access road, the soil fertility index, the credit access, and the variable club have a significant impact on technical inefficiency of farmers among farming systems in the slash and burn agriculture zone, while the educational level has only a significant impact on the technical inefficiency of the farmers practicing the maize mono-cropping system.

(Bozoglu, 2007) studied focusing on especially vegetable household production in Samsun province Turkey by using Stochastic frontier analysis. For Turkey, one of the main producer countries in the world. Thus, they defined the technical efficiency of household level and influencing factors (including the age of farmers, the experience of farmers, schooling, family size, off-farm income, credit use, and farm size) of technical inefficiency level. The study results showed that schooling, experience, credit use, women's' participation, and information score negatively influenced technical inefficiency, while age, family size, off-farm income, and farm size showed a positive relationship with inefficiency. Also, schooling, experience, information score, credit use, women's' participation in the exception of family size, farm size, and off-farm income had a significant. (Abdulai and Eberlin, 2001; Vasylieva and James, 2020) this study examines the significance of some major factors that are believed to influence levels of farm production and efficiency, including education, liquidity constraint, and experience. Although the importance of these factors has often been raised in policy debates on Nicaraguan agriculture. The study results reveal that larger families appear to be more efficient than smaller families, level of education, access to formal credit, family size, and tractor use each has a positive impact on efficiency. Participation in non-farm work, however, appears to have a negative effect on efficiency. The negative sign for the education variable indicates that higher levels of education increase efficiency. The negative and significant relationship between access to credit and inefficiency suggests that farmers who face credit constraints on purchased inputs experience higher technical inefficiency.

Battese and Coelli (1996) and Battese (1995) studied inefficiency factors for Indian farms and found that age, education, and farm size were important factors for the technical efficiency of Indian farms. They used two-stage SFA with panel data, that is they put in one model the production inputs and inefficiency determinants or factors. Results of their studies, land, labor, coefficient of the proportion of irrigated land are positive, reflecting the higher productivity of irrigated land. The coefficient of the ratio of hired labor to total labor, was negative, indicating that hired labor is less productive than family labor. Also, the age of farmers, education level, and coefficient of the year was a negative sign. For example, the older farmer tends to have smaller inefficiencies than younger farmers. For education, farmers with greater years of formal education tend to be more efficient in agricultural production. In other words, if greater these factors tend to be more efficient in agricultural production.

Stochastic frontier analysis

Efficiency concept is pioneered by Farrell (1957), there are two widely used methods of measuring the efficiency of a decision-making unit: The Data Envelopment Analysis (DEA) - non-parametric approach and the Stochastic Frontier Analysis (hereafter SFA)- parametric approach. The SFA approach independently proposed by Aigner and Lovell (1976) and Wim and Broeck (1977). The stochastic frontier production function has two error components: one is to account for the existence of technical inefficiency of production and the other one is express random error. The two-step estimation approach was utilized to early efficiency analysis, such as Bravo-Ureta and Pinheiro (1993), Kalirajan (1981). But this two-step estimation approach contradicts the assumption on the independence of inefficiency effects in the stochastic frontier model. The number of researchers solved this problem in their studies using a single-step estimation approach. For example Seok, Moon, Kim and Reed (2018), Nyemeck et al. (2008), Hung-Jen Wang (2002), Mehmet Bozoglu (2007), Battese (1995), Huang (1994), Reifschneider (1991), etc. The single-step estimation approach defined by the following equation.

$$y_i = \exp\left(f\left(x_i, \beta\right) + v_i - u_i\right) \tag{1}$$

Where y_i represents the household production, x_i denotes a set of inputs and β is parameters to be estimated, i is the ith household, v_i is the random error and distributed to be normal distribution as N(0; σ_v^2), and u_i is the non-negative random variable of the technical inefficiency part. The error component u_i needs to satisfy the assumption $u_{it} \geq 0$. The technical inefficiency function defined as:

$$\mu_i = \alpha z_i + w_i \quad (2)$$

Where μ_i is represented the mean of αz_i with truncation normal distribution at zero and σ^2 variance, α is estimated parameters, z_i is the technical inefficiency explanatory variables, and w_i is determined by the truncation of the normal distribution with zero mean and variance, σ_2. The Cobb-Douglas and Translog production function mostly dominate in stochastic frontier analysis using cross-section and panel data. For our estimation frontier production function described by following the Cobb-Douglas production function. The SFA model can be written as:

$$lny_i = \beta_0 + \sum_{j=1}^{5} \beta_j \, lnz_j + v_{it} - u_{it} \quad (3)$$

Where, *ln* is expressed natural logarithm, y_i is the total income from vegetable production of i[th] household, x_j is denotes of j[th] inputs, j is the number of inputs variables, j = 1, 2, 3 …. 5, namely, sown area (ha), seed cost (million MNT, MNT is the abbreviation of Mongolian currency tugrik, hereafter MNT), labor (man/days), used manure (ton), capital (million MNT) is aggregated value of total machinery cost plus total expenditure on machinery rent cost for cultivation, harvesting, manure, pesticide and diesel cost on cultivation, harvesting and transportation cost to market. β_0, β_j are to be estimated coefficients.

The technical inefficiency function is defined as:

$$\mu_i = \alpha_0 + \alpha_1 size + \alpha_2 age + \alpha_3 sex + \alpha_3 edu + \alpha_4 exp + \alpha_5 nfi + \alpha_6 cre + \alpha_7 lfi + w_i \quad (4)$$

Where, α is estimated parameters, *size* is the number of family members, *age* is the age of household leader, *sex* is the household head's sex, which is variable value is one if has female, two is male, *edu* is the household head's education level, *exp* is the experience of a household heads in vegetable production, *nfi* is the non-farm income dummy variable (non-vegetable income = 1, otherwise 0), *cre* is the credit also dummy variable (if the household has a credit = 1, otherwise 0) and *lfi* is the land fragmentation index. Maximum-likelihood estimates of the parameters for the stochastic frontier production function were obtained using the Stata.14 computer program. An important test to check the existence of the technical inefficiency exists is one-sided error specification. This amount to a test for the presence of u_i in the model, and a generalized likelihood ratio (LR) test for the null hypothesis of no one-sided error can be constructed based on the log-likelihood values of the OLS (restricted) and the SF (unrestricted) model. The LR test statistic is -2[$L(H_0)$ - $L(H_1)$], where $L(H_0)$ and $L(H_1)$ are log-likelihood values of the restricted model and the unrestricted model, respectively, and the degree of freedom equals the number of restrictions in the test (Kumbhakar, Wang, and Horncastle, 2015).

Description of data collection area: Mongolia is located in Central Asia and has a total area of 1564.2 thous.km square. It is divided into five sized economic regions, namely Western, Khangai, Central, Eastern, and Ulaanbaatar area. The country consists of 21 provinces and the capital city. The provinces are divided into 330 soums (sub-provinces). The Mongolian population is nearly 3.2 million, while the population density was 2 persons per kilometer, but 311 persons per kilometer in Ulaanbaatar (NSO, 2017). Mongolia has an extreme climatic condition. The country is dryland and has a low level of precipitation (average is from 250 to 400 mm a year), and absolutely temperature is from -28° to -54° Celsius in winter and from +40° to +45° Celsius in the summer. The vegetable main growing area is the Western and Central regions. Currently, vegetable household production consists of approximately 80 percent of total vegetable production in Mongolia. Also, there were 15862 households and 1422 enterprises (National Statistics Office of Mongolia, 2018). Vegetable household is mainly growing potato, carrot, turnips, cabbage, onion, garlic, cucumber, tomato, watermelon, and melons.

Descriptive statistics for variables: To examine the technical efficiency of vegetable household production, primary data was collected through a semi-structured questionnaire using a random sample technique. Our research was carried out between November 2019 and January 2020. The total random sample was 300 vegetable households. The response rate was 86.7%. For the household production function, we use one output- sales income of the household and four inputs including sown area, seed cost, labor, and capital. Sales income calculated by household vegetable sales income, price, and sales quantity were gathered from the household. All vegetable sales were aggregated into one output value (Mongolian tugrik, hereafter MNT).

Sown area, labor, and used manure are measured in hectare (ha), man/days, and ton respectively. Therefore, capital and seed costs are accounted for in value terms. We calculated capital including the value of cash expenditures on manure, pesticide, maintenance, diesel cost for transportation, cultivation, and harvesting, rental machinery cost within the year, measured as the sum of depreciation of machinery. The annual depreciation of machinery was calculated by the straight-line method. Table 1 shows the summary statistics of our variables. Vegetable household averaged approximately 2.03 ha and their sales income was 15.2 million MNT. The sample vegetable household average seed cost was 1.8 million MNT and average labor 179.6 man/days. Most of the household used to manure to cultivated areas. The sample household average used manure was 24.14 tons. For the capital, most of the household has a truck, car, and motorcycle. The average capital value was 15.3 million MNT.

In the technical inefficiency model, there were eight factors of household vegetable production. These explanatory variables have to choose based on previous studies. Sample vegetable households averaged 4.33 family members and 95% of the total household head was male. Our hypothesis for family size and head‘s sex are fewer family members more efficient than larger family and male‘s decision more than female in the household, respectively. For the education variable, if have education level has a higher, it enhances farm technical efficiency (Fuwa, Edmonds, and Banik, 2007). It shows that the education of the household head and, i.e. education value of one if household head is illiterate, two if has a primary school, three if has a secondary school, four if has associate and five is a bachelor (graduate university). Household head's averaged 46.7 years old and their experience in vegetable production was 15.3 years. Age and experience variables are indicated the possibility of farmers to adopt innovations and more technical skills. Thus, these variables negatively affected to technical inefficiency. We gathered data on non-farm income, it represents the relationship between technical efficiency and the existence of non-farm income. Because some of the households have another source of income. For example, in the exception of vegetable production, there has livestock and some of the family members work public sector and retirement. Non-farm income variable was a dummy if the household has a non-farm income is equal to 1, otherwise 0. Also, we check the relationship between technical inefficiency and credit use. Credit can help to increase technical efficiency because the household decides to overcome financial constraints for the purchase of inputs (Abdulai and Eberlin, 2001). For example, seed, rent a tractor during the cultivating period. Credit use indicates dummy variable if the household used credit to 1, otherwise 0. Sample vegetable households are growing comparative many vegetables including potato,

Variables	Mean	Standard deviation	Minimum	Maximum
Sales income, million MNT	15.17	12.04	1.50	74.20
Sown area, ha	2.03	1.62	0.088	10.00
Seed cost, million MNT	1.78	1.71	0.026	12.72
Labor man/days	179.57	140.27	25.00	873.62
Used manure, ton	24.14	28.30	2.00	160.00
Capital, million MNT	15.31	9.94	1.31	66.28
Family size	4.33	1.69	1	10
Household head's age	46.73	11.10	24	74
Household head's sex	1.95	0.21	1	2
Education	3.60	0.94	1	5
Owner's experience	15.34	9.61	2	42
Non-farm income	0.37	0.48	0	1
Credit use	0.73	0.44	0	1
Land fragmentation index	0.54	0.29	0.11	1.25

Notes: All the figures are based on randomly selected 260 households observations from Mongolia

Source: Field survey conducted in Mongolia

Table 1: Descriptive statistics of households' vegetable production in 2019.

carrot, cabbage, onion, garlic, tomato, cucumber, watermelon, and melons. The household sown area plot was higher and the land fragmentation average index was 0.54. The land plot is higher, which means the cause of inefficiency. But if the household could manage that, land fragmentation positively affected technical efficiency.

Results and discussion

Estimation of SFA model

The results of the estimated stochastic frontier function are presented in Table 2. We used the Maximum Likelihood Estimation (MLE) method to estimate the parameters of the stochastic production frontier and inefficiency effect models jointly in a single-stage estimation procedure. Also, we tested there is technical inefficiency exists or not can be conducted by the null hypothesis. The estimated value of the variance parameter of the model (γ) was close to 1 (γ = 0.89), indicating that an inefficiency exists. Based on the likelihood ratio (LR) test was higher than the critic value (LR = 36.28) and LR test rejected the null hypothesis (Kumbhakar et al., 2015). In other words, there are technical inefficiency effects exist and stochastic. The result of the estimation of the SFA model showed an expected sign of variables and all variables were significant in the frontier function. A 1 % increase in the land area increased output by 0.26 % while a 1% increase in labor and seed cost increased output by 0.42% and 0.13% respectively.

Also, a 1 % increase in manure and capital increased output by 0.12 % and 0.14 % respectively. The land and labor were the highest effects on the output followed by seed cost and capital. It means that the land and labor are major influencing factors of the vegetable production. This result was reported by Bozoglu and Ceyhan (2007), Anang et al. (2016), and Abdulai and Eberlin (2001). Those authors found that the main highest influencing factors are land and labor in crop production. The sum of the values of the inputs is 1.07 which means that increasing returns to scale for vegetable household production in Mongolia. As a result, if all inputs by 1 % will increase vegetable output by 1.07 %.

The technical efficiency's score was estimated between 43.2% and 99.9% (average 0.646). The mean technical efficiency was 64.6 percent, which means that the maximum output of vegetable household production. In other words, a vegetable household will lose about 35.4 percent

	Variables	Coefficient	Standard error
Frontier function	*lnland*	0.256***	0.054
	lnlabor	0.418***	0.032
	lnseedcost	0.131***	0.035
	lnmanure	0.122***	0.033
	lncapital	0.135***	0.049
Inefficiency effect	*Family size*	0.131*	0.069
	Household head's age	-0.232	0.153
	Household head's sex	-0.020	0.133
	Education	0.012	0.063
	Household head's experience	-0.102**	0.052
	Non-farm income	-0.155**	0.066
	Credit use	-0.078	0.067
	Land fragmentation index	0.205***	0.065
	Constant	1.526**	0.632
	Observations	260	
	σ_u^2	1.68	
	σ_v^2	0.2***	
	Log-likelihood	-160.19	

Notes: *, **, *** are 10, 5 and 1% significance levels respectively

Source: Stata's result with truncated normal distribution

Table 2: Maximum likelihood estimation of the Cobb-Douglas stochastic frontier production function and inefficiency model for a vegetable household in Mongolia.

of the potential output due to technical inefficiency. The 40 percent of the sample households had technical efficiency level below 0.6 (or 60%), whereas 50.8 percent of the household had technical efficiency level between 0.61-0.8 (or between 61-80%), the rest of household had technical efficiency level more than 0.81 (or 81%) (Figure 1). In other words, 90.8 percent of sample vegetable household technical efficiency level was below than 0.8.

Based on technical efficiency level results, we determined to mean technical efficiency level concerning land size (sown area) (Table 3). The study revealed that households with large plots of land are more technically efficient at producing vegetables than households with small and medium-sized plots of land. This finding is confirmed by the study of (Battese Coelli, 1996), (Asefa, 2011). However, some of the researchers found that small farms are more efficient (Masterson, 2007), Bozoglu and Ceyhan (2007).

	Technical efficiency
Small (0-2 ha)	0.65
Medium (2-5 ha)	0.64
Large (more than 5 ha)	0.66

Source: Calculation result

Table 3: Mean efficiency level, by household's land size.

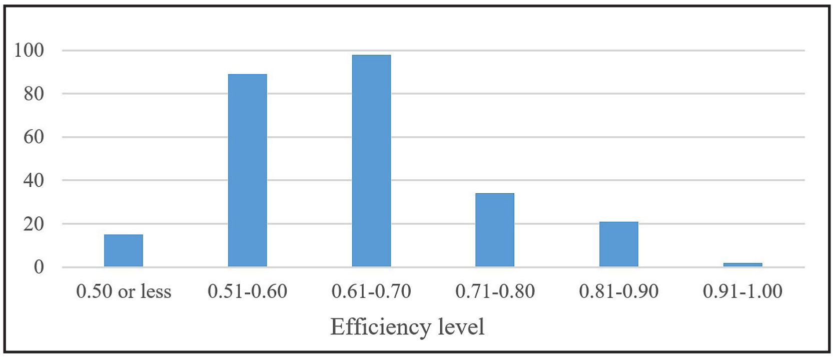
Technical inefficiency analysis

The result of the inefficiency model (Table 2) indicated the effect of explanatory variables to technical inefficiency, and the number of the variables including family size, household head's experience, non-farm income, and land fragmentation index were significant with the exception of the household head's age, sex, education, and credit use. A negative sign on a parameter that is explaining technical inefficiencies means that the variable is decreasing technical inefficiency (or improving efficiency), while for a positive sign the reverse is true.

The family size positively affected technical inefficiency. It is clearly showed that a smaller family (fewer members) is more efficient than a larger family. This finding is consistent with the work of Bravo-Ureta and Pinheiro (1993). Some empirical studies' result show larger families appear to be more efficient than smaller families. For example, Abdulai and Eberlin (2001) mentioned that larger family size has a more expensive (i.e. for clothing and food comparative to the small member), but it ensures the possibility of enough family labor for farm operations.

The negative sign of experience variable, which indicated that households heads had more experience leading to improving efficiency, a finding that is consistent with the results reported in 3 studies (Bozoglu and Ceyhan (2007); Anang, Tetteh, Bäckman and Sipiläinen, 2016; Addai and Owusu, 2014).

Non-farm income had a negative coefficient and highly affected technical inefficiency more than other variables. In other words, if a household earns more non-farm income that is causing more efficient production. The households sampled sampled for our study answered that non-farm income (including salary, pension, and other activities income) has been spent on vegetable production activities like an investment. However, most of the empirical results have shown a positive relationship between non-farm income and technical inefficiency (Laha, 2006; Asefa, 2011, Anang et al., 2016; Abdulai and Eberlin, 2001; Addai and Owusu, 2014). They mentioned that in greater non-farm activities tend to exhibit higher



Source: Estimated technical efficiency from Stata

Figure 1: Technical efficiency distribution of vegetable household's production in Mongolia, 2019.

levels of inefficiency because family members need to reallocate time for farm activities.

Besides, the land fragmentation index also has significant and positive sign of the coefficient. It means that larger plots may cause an increase in inefficiency. But if the management is better, it causes a positive impact on technical efficiency (Tan et al., 2010). Some of the authors found that the land fragmentation index impact too negatively (Kiprop et al., 2015).

Household head's age, sex, education, and credit use variables were negative and insignificant. There was a negative relationship between age and inefficiency, which means that older farmers were more efficient than younger ones. Some of the researchers have revealed conflicting results. For example, older farmers are more efficient in some studies (Battese, 1995; Broca, 1997), while other authors found younger farmers are more efficient (Abdulai and Eberlin, 2001; Bozoglu and Ceyhan, 2007; Seok et al., 2018). 95 percent of the total sampled vegetable household head was male. For the sex variable sign was negative as expected. This result is similar to some author's results (Anang et al., 2016). They found that males make better decisions than females in the household. Many researchers studied women's participation in household production. For example, (Bozoglu and Ceyhan, 2007) studied women's participation in vegetable production of Turkey. They found that higher women's participation is caused less efficiency.

The coefficient of education was negative to technical inefficiency. When education level is higher, it enhances farm technical efficiency and more educated farmers get enough information than low educated farmers. This result reveals that educated farmers are more likely to reduce their technical inefficiency. This finding also confirmed the result of (Fuwa et al., 2007).

The credit use coefficient sign was negative but insignificant, this means that credit is showed that gives good opportunities for improving technical efficiency. This finding was similar to result from other studies (Bozoglu and Ceyhan, 2007; Asefa, 2011; Laha, 2006; Addai and Owusu, 2014). The Mongolian government implements low-interest-rate credit with long term machinery loans and seed loan programs to increase vegetable production. But most of the sampled households answered that they could not access this credit. Because the credit is not enough and does not access the target group. Thus, vegetable household have to access higher rate credit during the cultivating period to purchase seed and financing for other costs (like renting a tractor for cultivation).

Conclusion

The main goal of this paper was to determine the technical efficiency of vegetable households in Mongolia by using stochastic production frontier analysis. Our study using survey data was obtained from randomly selected 260 vegetable households in the main growing areas in Mongolia. As a result of our comparative efficiency analysis, the mean technical efficiency of the household was 0.64. This result suggests that this sample of the household could increase their output or decrease inputs through better use of available resources given the existing technology in the research area. Based on our technical efficiency results, only 9.2 percent of the sampled household technical efficiency level was higher than 90 percent.

The inefficiency model, explanatory variables are family size, household head's experience, non-farm income, and land fragmentation index were significant variables for positively affected technical efficiency. Other variables are the household head's age, sex, education, and credit use were insignificant and negative.

The main four findings are based on our study for vegetable production in Mongolia. First, the land and labor are main influencing factors in vegetable production. Second, the larger farmland (more than 5 ha) vegetable household are more efficient than small and medium sized farmland. Third, we found the positive impact of the experience of the household head on efficiency. Also, if the household has a larger non-farm income, it may cause improving technical efficiency. Thus, household needs another source of income. Finally, many types of vegetables growing households are more efficient than only one type of vegetable growing households. In addition, one of the important variables as a proxy for government policy was credit. Our study result found that credit use positively affected technical efficiency and insignificant.

Overall, this study tried to indicate the technical efficiency of vegetable household production and explore to determining factors of technical inefficiency first time in Mongolia. Furthermore, the government will apply this study to strengthen the agriculture policy at national level in Mongolia.

Future studies should seek how to include new technologies (Sieja and Wach, 2019) and the omgoing industrial revolution achievements (Rymarczyk, 2020; Modz, 2018) into the research on the efficiency production of farms.

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