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Comparison of Agricultural Costs Prediction Approaches

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Abstract

The paper submitted offers an assessment and comparison of three approaches to agricultural cost inputs short-term forecasting, that have been proposed as possible alternatives to tackle the problem. The data applied have been taken from the Czech Statistical Office and the Farm Accountancy Data Network data sources. The forecasts were prepared using time series analyses based on methods of exponential smoothing and Box-Jenkins methodology of autoregressive integrated process moving averages. The proposed change index numbers for the 2012, 2013 and 2014 years from three approaches were confronted with the real development of costs time series as it was found in the statistical FADN survey results. The main conclusion drawn pointed out that, for the purpose of economic income estimation based on the FADN database, the cost prediction approach based on the same database, i.e., on time series analysis of the FADN panel data, is the most applicable one. However, it is recommended, too, to use other approaches for crops protection products cost and labour cost development.

Keywords

Time series analysis, exponential smoothing, ARIMA models, cost inputs in agriculture, Farm Accountancy Data Network (FADN).

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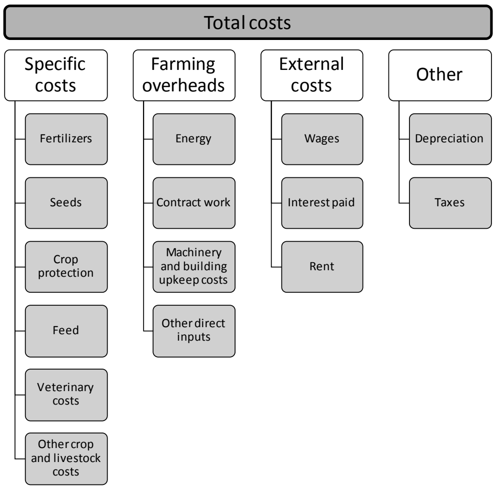
Introduction

The business development in agriculture considers the economic, environmental and social sustainability, based on the fundamental functions of agriculture for life in the landscape and society. For assessment of the economic sustainability of agriculture usually the production outcomes are considered, incomes in the shape of subsidies and the cost inputs. Applying this set of information, the economy results can then be expressed using various indicators.

Among those most important belongs the multi-factor productivity rate (the ratio of agricultural outputs to agricultural inputs), which is employed using various approaches for performance appraisal of agricultural holdings (Kostlivý et al., 2017) on the one side, and for agricultural policies assessment on the other side (Quiroga et al., 2017; Rizov et al., 2013). Another important measure of the final economy outcome is income, that can be expressed, e.g., using indicators of the type of Farm Net Value Added or Farm Net Income (European Commission – FADN EU, 2016) having been applied in many differently aimed analytical works (Špička, 2014; Deppermann et al., 2016). To support the management of agricultural holdings and the assessment of planned agricultural policies, a model has been formed based on the micro-economic data from the FADN network in the Czech Republic, for estimation of the economic outcomes of agriculture, using the indicators mentioned above (Hloušková et al., 2014). The paper presented here is dealing with the partial problem of year-on-year change of selected cost items, with the intention to submit a recommendation for agricultural incomes estimation modeling in its complex.

Costs can be sorted according to various viewpoints. The present text is considering the approach to costs sorting that is applied in the FADN and displayed in the Figure 1. The total costs are subdivided into Specific costs, Farming overheads, External costs and Other costs. The external costs are applied in the Family Farm Income indicator evaluation, what corresponds to profit after wages, interest and renting costs subtraction, and investment subsidies addition, less the investment tax. The biggest portion of the total costs is represented by intermediate consumption, set up of specific costs and farming overheads (European Commission – EU FADN, 2016). European Commission (2016) states that seeds, feed, energy and fertilizers belong among the intermediate consumption main costs; the long-term depreciation prediction (European Commission, 2016) is based on the production and inflation development function, and for costs projection the macro-economic data from the Economic Accounts for Agriculture are employed.

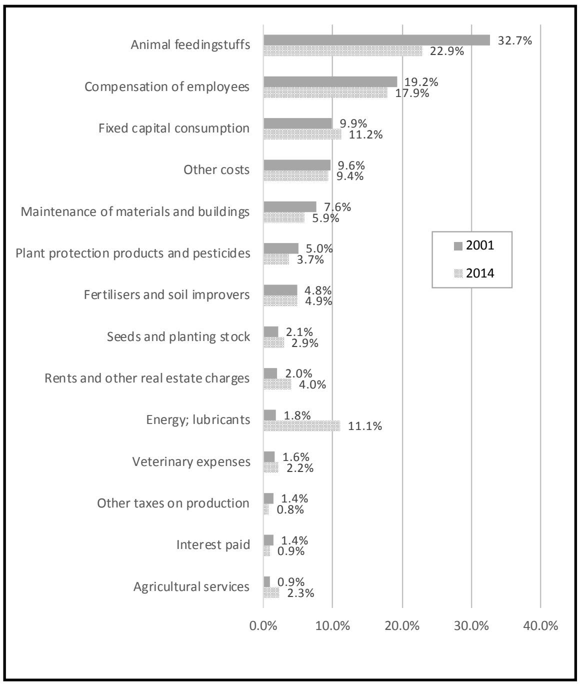


Source: own processing based on FADN methodology

Figure 1: Costs sorting scheme.

As a target of the paper presented, a comparison of the three approaches to the short-term prediction of cost inputs into agriculture can be assumed, and selection of the most suitable method for the cost component given. Solutions of the year-on-year prediction considered start from various data sources and different methods use. As data sources, the macro-economic data from the Czech Statistical Office (CZSO) and the micro-economic data from the Farm Accountancy Data Network in the Czech Republic (FADN CZ) have been applied. Among the cost items tested there are seed costs, fertilizers, crop protection, electricity costs, wages, and rent paid.

The shares of separate cost types on the total costs and the development of these between 2001 and 2014 years is presented in Figure 2. During that period, a significant reduction could have been observed of the cost shares on feed, pesticides, wages and maintenance of machinery and buildings. On the other hand, the shares of cost items on depreciation, renting, energy, seeds and agricultural services have risen. The fertilizer costs share remains the same. These changes observed are related to the development of agriculture´s structure and of the market environment.



Source: own processing based on Economic Accounts for Agriculture (CZSO)

Figure 2: Shares of cost items on the total costs (%).

Processing predictions in agriculture is complex in general, since the results are often affected by unforeseeable circumstances. In particular, it is the development of weather, infection situations in animal breeds, political instability (Allen, 1994) and unexpected changes in global development. These phenomena have an impact not only upon the agricultural production quality and quantity but upon the agricultural commodities market prices, too, the market situation, the consumer behaviour, and last but not least, upon the cost-input prices. In recent years there have been large fluctuations in commodity prices, which pose a problem in developing strategies both for farmers and agribusiness entrepreneurs and for policy makers (Khalid et al., 2014). For example, seed costs and feed costs belong among the basic costs of production consumption that are closely related to the results of agricultural production.

The specifics of agriculture should be reflected not only in modeling but for all the kinds of analyses (Allen, 1994). Usually, data on crop yields, numbers of animals or agricultural prices have been predicted using the time series in agriculture (Allen, 1994; Labys, 2003; Ishaque and Ziblim, 2013; Hamjah, 2014). For forecasting purposes, the exponential smoothing methods and the autoregressive integrated moving average (ARIMA) have been used in modeling most frequently. In case of cost prediction, it is advisable to consult research outside the field of agriculture, too. Many works have been dedicated to the crude oil prices projection, where E et al. (2017) have arrived with a combination of the variational mode decomposition methods, independent component analysis and ARIMA methods, whereby more precise forecasts have been reached.

In agriculture, medium-term and short-term forecasts have been applied (European Commission, 2017) or, forward-looking forecasts (European Commission, 2016; OECD, 2017). The present paper offers forecasts of change index numbers for one year ahead, i.e., it is a short-term forecast. Exponential smoothing methods and the Box-Jenkins autoregressive integrated processes methodology have been applied in the processing proper. The index numbers predicted have been compared with the actual time series development of the separate costs using the method of differences and totals, as it had been disclosed from the FADN statistical survey outcomes. This way, the most appropriate approach to the costs estimate has been found subsequently, and the resulting recommendation for the separate cost items forecast presented.

The main finding of the contribution is then the recommendation for use of the data source as well as the procedure for prediction processing of the cost component, which is a part of the comprehensive estimate of the income results of agricultural enterprises based on FADN CZ data.

Materials and methods

Three ways are accessible for prediction of the cost variables employed by the FADN method in the Czech Republic, in the business outcomes estimation.

Firstly, (***i***), it is possible to apply index numbers from the Czech Statistical Office output "Input agricultural price indices (corresponding period of previous year = 100)". A disadvantage of this approach, anyway, is in the late availability of the data – these are published quarterly with one-and-half month lag. It means, the information on index development during the estimated year could be available in the middle of February next year. The farm income prediction methodology has applied in the cost items estimation the "Input agricultural price indices" for the 3rd quarter of the year, which then was available at mid-November of the year estimated, from the Czech Statistical Office public database (Hloušková et al., 2014). Nevertheless, this index does not contain the cost prices development over the last three months of the year.

As a second approach (***ii***), the cost items time series panel data forecast from FADN database in the CR was identified. Results of this processing have been presented by Hloušková et al. (2015) in their final report. The process designed utilizes the population of panel data in time series since 2001. The basic advantage of panel data application is the reduction of impact of farm variation within the sample, upon results of the forecast. Among other advantages mentioned by Hsiao (2014) are, e.g., "more accurate predictions for individual outcomes", or, "providing micro-foundations for aggregate data analysis". Both the advantages of panel data mentioned have been utilized by the methodology described above in obtaining an accurate estimate of the representative FADN sample, generalized by weights and subsequently aggregated upon the level of the entire CR agriculture.

By the third way (***iii***), the prediction is utilized based on the time series of cost items in current prices from the Economic Accounts for Agriculture (EAA) published by CZSO. Prediction modeling based on the EAA data (CZSO, 2016b) has been performed within this paper. The time series available publicly contains data since 2001. STATISTICA CZ 12 programme has been employed in the processing.

In the second (***ii***) and third (***iii***) approaches, five models for data prediction in short time horizon have been applied, i.e., one-year prediction has been performed based on annual time series:

1. ARIMA (1,1,0), time series stationarisation by means of the first difference, autoregression parameter 1, with Melard method of exact estimate;
2. ARIMA (1,1,0), without estimate of the constant, stationarisation by means of the first difference, autoregression parameter 1, with Melard method of exact estimate;
3. Linear Holt exponential smoothing, without seasonal component, level smoothing parameter $\alpha = 0.1$, trend smoothing parameter $\beta = 0.1$;
4. Smoothing of the time series by means of Fourier transformation, ARIMA (1,1,0), time series stationarisation by means of the first difference, autoregression parameter 1, with Melard method of exact estimate;

5. Smoothing of the time series by means of Fourier transformation, linear Holt exponential smoothing, without seasonal component, level smoothing parameter α = 0.1, trend smoothing parameter β = 0.1.

Six cost items obtained from the resources given above have been processed in comparison of the indices change. These are: purchased seed and seedlings, purchased fertilizers, plant protection costs, electrical energy, personal costs and renting costs. In order to obtain the change index numbers, time series since 2001 have been applied in the ***ii*** and ***iii*** approaches. The results have been verified on actual data from the given periods by means of differences and totals. To obtain reliable conclusions, testing has been performed for three years predicted, 2012, 2013 and 2014.

Advanced time series analysis adaptive techniques have been employed in the processing. Adaptive time series smoothing procedures using different parameters in separate short sections can be applied in such a case, when the time series cannot be explained by one function, i.e., the trend function is changing in time and it does not have constant parameters. When using the adaptive models, it is supposed that, the most up-to-date data have the strongest impact upon future development. Therefore, the most up-to-date data are preferred here, and older information in the time series given is assigned lower weights. For example, the method of moving averages or the exponential smoothing method can be included here. When shorter time series, typical for all the three varieties compared in this work become the object of study, among the various methods, e.g., the exponential smoothing method can be applied (Artlová and Artl, 1995). Using weighted averages, weights are assigned to separate observations and the weights become exponentially reduced, i.e., the lowest weights become linked to the oldest observations. We can then distinguish between simple exponential smoothing, double (Brown) exponential smoothing or Holt linear exponential smoothing.

Using the expanded simple exponential smoothing Holt succeeded already in 1957 at predicting time series with a trend. The Holt linear exponential smoothing model is composed of the balancing equation for estimation of the linear trend level in time t and of the balancing equation for estimation of the linear trend angle in time *t*, for h = 1, 2, ... and it can be expressed as

$$\hat{y}_t = l_t + hb_t \quad (1)$$

where the estimate of the level is equal to

$$l_t = \alpha y_t + (1-\alpha) * (l_{t-1} + b_{t-1}) \quad (2)$$

and the trend estimate can be derived from

$$b_t = \beta^*(l_t + l_{t-1}) + (1-\beta^*)b_{t-1} \quad (3)$$

where α is the level equalizing constant ($0 \leq \alpha \leq 1$) and $\beta*$ is the trend equalizing constant ($0 \leq \beta* \leq 1$) (Hyndman and Athanasopoulos, 2013).

Another approach applied in time series forecasting in this work is the Box-Jenkins methodology of moving averages autoregressive integrated processes, called ARIMA modeling.

The aim of the models is to describe autocorrelation in the data. Autocorrelation informs about the power of linear relationship between random variables, where each observation is composed of the random error component (random shock) and a linear combination of previous observations. Partial autocorrelation cleans the random quantities from the impact of quantities situated among them. Applying graphical expression of autocorrelation, it can be simply discovered, whether the time series is a stationary one (Artl et al. 2002).

The Box-Jenkins methodology is assuming time series stationarity. As far as the time series properties are not dependent upon time of the series studied, the series can be considered a stationary one. Time series with trends or with seasonality are not stationary, since trend and seasonality should influence the time series values at different times. Conversely, a time series with white noise processes is stationary. Stationary processes are not frequent, therefore various methods can be applied in time series stabilization. One of these is the differentiation, where differences between subsequent observations are evaluated (Linden et al., 2003). In time series smoothing the Fourier transformation has been applied, too, so far used in commodity prices modeling in agricultural issues, e.g., by Enders and Holt (2012).

ARIMA models are based on the moving average processes (MA) and on autocorrelation processes (AR) and contain three parameters: *p, d* and *q*. The writing of such a model is done as ARIMA (*p, d, q*), where *p* is the autoregression parameter, *d* means the number of differentiations and by *q* is the moving average (Mošová, 2013).

The verification that, a function is not autocorrelated, has been done by means of graphical expression of the residual autocorrelation function (ACF), which is the expression of linear dependence of lagged values (horizontal axis) on autocorrelation coefficients of the residues rk (vertical axis).

The non-systematic component is not autocorrelated in case, that none of the autocorrelation coefficients exceeds the limits of 95% confidence interval $(\frac{-2}{\sqrt{T}}, \frac{2}{\sqrt{T}})$. In case, that annual time series are being analysed, it is recommended to use time series length of 30 years or more (Hanke and Wichern, 2008; StatSoft, 2013), which may be misleading in some cases. As Hyndman and Kostenko (2007) state, the time series length depends especially on data variation and number of applied parameters. The problem of EAA and FADN data use are short time series, available since 2001 only. They are annual time series unable to expand and not containing the seasonal component. Considering absence of other data sources at such a high discrimination level of cost items and taking into account the relevant outcomes, the methods applied at selected cost items have not been refused despite the risk of a less exact model construction.

Results and discussion

The solution is presenting a comparison of outcomes of the three approaches described above, in processing of development forecasts of selected cost items, where the predicted change index numbers have been confronted with the actual FADN results over the 2012-2014 period.

The change index numbers for the first approach (***i***) have been taken over from the published estimates of the year-on-year change in the inputs into agriculture quarterly index numbers (CZSO, 2016a). Change index numbers for the second approach (***ii***) have been taken over from the outputs of internal research project titled "Estimation of economic results in agriculture with low or null information on development in predicted year based on FADN" (Hloušková et al., 2015). The index numbers for the third designed approach (***iii***), which have been derived from the Economic Accounts for Agriculture (CZSO, 2016b), have been processed as part of this study based on the time series analysis methodology as given above.

The comparison of results of the selected cost items change index numbers considered for use in the micro-economic model of the agricultural income estimate based on FADN CZ is presented in Table 1. This table contains the actual year-on-year change index numbers, too, based on the results of finished FADN surveys. Results for the 2012, 2013 and 2014 years estimates have been compared here. Within the (***ii***) and (***iii***) approaches the analysis based on 10-year, 11-year and 12-year time series of year-on-year index numbers, begun within the 2002/2001 period, has been presented.

Most frequently, in fifteen cases, the ARIMA (1,1,0) method has been applied for forecasting. In eight cases the ARIMA (1,1,0) method with smoothing has been used. In six cases the ARIMA (1,1,0) constant-free method and the Holt linear exponential smoothing have been used. In one case, the Holt linear exponential smoothing method with time series smoothing using transformation has been used.

In the next step, deviations of each index number predicted from the actual year-on-year change of the cost items results registered by FADN survey were evaluated. The deviations are compared in Table 2, where the best fitting predictions for every cost item and period are highlighted in bold figures. Most occurrences with the lowest deviation from reality observed have been identified within the second approach which is based on time series analysis methods applied on the FADN CZ panel data. This approach suits best in the seed costs and renting forecasts. The first approach

Indicator predicted	Period	Approach	Index number predicted	Method (source)	Actual index number (2)
Seed and seedlings	2012/2011	*i*	1.0350	(1)	1.0735
		ii	1.0491	3 (3)	
		iii	1.0367	1 (4)	
	2013/2012	*i*	1.0780	(1)	1.0341
		ii	1.0132	3 (3)	
		iii	1.1290	3 (4)	
	2014/2013	*i*	0.9770	(1)	1.0152
		ii	1.0186	3 (3)	
		iii	1.0276	1 (4)	

Note: (1) Change index number taken from CZSO (2016a), (2) Change index number of weighted FADN results, (3) Change index number taken from Hloušková et al. (2015), (4) Own processing, data source CZSO (2016b), NA: not available

Source: own processing based on FADN methodology

Table 1: Results of change index numbers (to be continued).

Indicator predicted	Period	Approach	Index number predicted	Method (source)	Actual index number (2)
Fertilizers and soil improvers	2012/2011	*i*	1.1240	(1)	1.0972
		ii	1.0151	4 (3)	
		iii	1.0282	1 (4)	
	2013/2012	*i*	1.0310	(1)	1.1289
		ii	1.0482	4 (3)	
		iii	1.0167	1 (4)	
	2014/2013	*i*	0.9360	(1)	1.0146
		ii	1.0350	4 (3)	
		iii	1.0189	1 (4)	
Plant protection products	2012/2011	*i*	1.0780	(1)	1.0603
		ii	1.0123	4 (3)	
		iii	1.0006	1 (4)	
	2013/2012	*i*	1.0340	(1)	1.0823
		ii	1.0249	4 (3)	
		iii	0.9708	5 (4)	
	2014/2013	*i*	1.0200	(1)	1.0671
		ii	1.0204	4 (3)	
		iii	0.9912	1 (4)	
Electrical energy	2012/2011	*i*	1.0830	(1)	0.9733
		ii	0.9833	4 (3)	
		iii	1.0198	2 (4)	
	2013/2012	*i*	1.0310	(1)	1.0386
		ii	1.0017	1 (3)	
		iii	1.1137	2 (4)	
	2014/2013	*i*	0.8860	(1)	0.9118
		ii	1.0020	1 (3)	
		iii	1.0037	2 (4)	
Wages paid	2012/2011	*i*	*NA*		1.0358
		ii	1.0109	1 (3)	
		iii	1.0305	3 (4)	
	2013/2012	*i*	*NA*		1.0335
		ii	1.0123	1 (3)	
		iii	1.0249	3 (4)	
	2014/2013	*i*	*NA*		1.0557
		ii	1.0124	1 (3)	
		iii	1.0092	1 (4)	
Rent paid	2012/2011	*i*	*NA*		1.0772
		ii	1.0543	1 (3)	
		iii	1.0433	2 (4)	
	2013/2012	*i*	*NA*		1.1324
		ii	1.0515	1 (3)	
		iii	1.0319	2 (4)	
	2014/2013	*i*	*NA*		1.1078
		ii	1.0477	4 (3)	
		iii	1.0618	2 (4)	

Note: (1) Change index number taken from CZSO (2016a), (2) Change index number of weighted FADN results, (3) Change index number taken from Hloušková et al. (2015), (4) Own processing, data source CZSO (2016b), NA: not available
Source: own processing based on FADN methodology
Table 1: Results of change index numbers (continuation).

(***i***) has estimated the index numbers best in five cases and in case of the third approach, the lowest deviations then have been found in four cases only. For the wages cost change forecast over 2014/2013 almost identical deviations have been found both in the second and third approach cases. Seed forecast for the 2012/2011 period has been obtained very similar in the first and third approach cases. The plant protection products forecast for 2014/2013 is similar for the first and second approach cases.

The lowest mean deviation over all the three approaches compared has been obtained in case of the wages costs. On the contrary, the highest mean differences between predicted and actual year-on-year index numbers have been obtained in fertilizer and electrical energy cost variables. For wages and renting costs the information on agricultural inputs prices index numbers from CZSO is not available, since this data source does not contain the items mentioned.

The amounts of average absolute deviation over all the periods tested for separate cost items (Table 3) define the approach (***ii***) as the best suited one (the analysis of FADN panel data), since four cost items from the total of six items studied have been predicted most accurately. The wages costs development, on the contrary, is best predicted by means of the (***iii***) approach based on the CZSO macro-economic data time series analysis. As an interesting outcome, the most accurate prediction of plant protection products by means of the (***i***) approach has been discovered, where the "Input agricultural price indices" from the first two quarters of the year estimated have been applied (CZSO).

Indicator predicted	Period	Approach		
		i	ii	iii
Seed and seedlings	2012/2011	-0.0385	**-0.0244**	-0.0368
	2013/2012	0.0439	**-0.0209**	0.0949
	2014/2013	-0.0382	**0.0034**	0.0124
Fertilizers and soil improvers	2012/2011	**0.0268**	-0.0821	-0.0690
	2013/2012	-0.0979	**-0.0807**	-0.1122
	2014/2013	-0.0786	0.0204	**0.0043**
Plant protection products	2012/2011	**0.0177**	-0.0480	-0.0597
	2013/2012	**-0.0483**	-0.0574	-0.1115
	2014/2013	-0.0471	**-0.0467**	-0.0759
Electrical energy	2012/2011	0.1097	**0.0100**	0.0465
	2013/2012	**-0.0076**	-0.0369	0.0751
	2014/2013	**-0.0258**	0.0902	0.0919
Wages paid	2012/2011	NA	-0.0249	**-0.0053**
	2013/2012	NA	-0.0212	**-0.0086**
	2014/2013	NA	**-0.0433**	-0.0465
Rent paid	2012/2011	NA	**-0.0229**	-0.0339
	2013/2012	NA	**-0.0809**	-0.1005
	2014/2013	NA	-0.0601	**-0.0460**
The number of occurrences with the lowest deviation		5	9	4

Source: own processing based on FADN methodology

Table 2: Resulting comparison of approaches.

Indicator predicted	i	ii	iii
Seed and seedlings	0.0402	0.0162	0.0480
Fertilizers and soil improvers	0.0678	0.0611	0.0618
Plant protection products	0.0377	0.0507	0.0824
Electrical energy	0.0477	0.0457	0.0712
Wages paid		0.0298	0.0201
Rent paid		0.0546	0.0601

Source: own processing based on FADN methodology

Table 3: Comparison of deviation averages.

Estimates of economic results of agriculture processed based on the FADN database micro-economic modeling have been presented e.g. by the Natural Resources Institute Finland (2016), where the average agricultural production purchase price index numbers have been employed in the cost development forecasts. As far as plant protection products are concerned, the methodology designed here suits better for the Czech Republic environment needs than the Great Britain approach. This type of estimates is prepared there within the Farm Business Survey (Rural Business Research, 2016) based on the FADN statistical survey. However, plant protection costs are considered at the same amounts as in the last year, because the amounts spent on plant protection are not connected with input costs (oil, natural gas) whose market prices are available. This approach applies the so-called naive forecasting, presuming that, the costs in future years will be at the same height as it is known from the most up-to-date information.

In the USA the income forecasts in agriculture are processed within the Farm Sector Income Forecast (USDA, 2016), where, as data source, the Agricultural Resource Management Survey at farm level is employed.

Other input information is consulted with agricultural project design macro-economic outputs (Agricultural Baseline Projection). Here, e.g., a projection of energy costs until 2025 has been prepared, expecting that, lower prices of oil and gas will bring about a decrease of costs in agriculture, which in particular concerns fertilizers and fuel.

In Canada, the Canadian Agricultural Dynamic Microsimulation Model (CADMS) has been applied, supplying forecasts concerning sales, costs and business assets at enterprise level. The model outcomes, inter alia, offer an overview of revenues in a more detailed shape, what is the value added of this model (Galbraith et al., 2011).

Conclusion

In the Czech Republic, there are limited information sources on prices of the separate cost items entering the production process of agricultural enterprises. For trend determination in the development of costs two relevant sources of representative data are available. These are the CZSO macro-economic data and the FADN CZ micro-economic data.

Outcomes of the studied issues bring new knowledge on the chances of costs forecasting in agriculture. Through comparison of the three approaches designed, differing in processing methodology and input information, it was discovered that, for agriculture income estimation based on the FADN database, the second approach (***ii***), based on the FADN panel data time series analysis, is the best applicable one. The advantage of this approach for the given purpose is data availability. In particular, current data available at the moment of application. Moreover, data can be subdivided in various categories according to needs, and the development of costs can be distinguished by the various enterprise size groups or production farm type. It has been confirmed that, good outcomes can be obtained applying time series of several cost item types, available in FADN CZ database since 2001.

However, other conclusions include the finding that not only one of the tested methodologies can be selected to predict various cost types, even though one approach is identified as the most accurate in many cases tested. When processing a short-term estimate, the cost type has to be taken in account. Based on the results, the "Input agricultural price indices" from the CZSO can be recommended for plant protection products development estimates, that have been found most accurate. The plant protection products time series is not suitable for future development forecasting, using the time series analysis described above, from none of the data sources applied. The development of fertilizer costs, which in each test period approached the real development of another tested technique, appears unclear. On the contrary, the third procedure approach, (***iii***), based on the Economic Accounts for Agriculture time series analysis, has been recommended for the wages costs future development.

The conclusions coming out from the presented paper set up an important background for updating the current methodical approach of the agriculture results estimation based on the FADN data.

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References

[1] Allen, P. G. (1994) „Economic forecasting in agriculture“, *International Journal of Forecasting*, Vol. 10, No.1, pp. 81-135. ISSN 0169-2070. DOI 10.1016/0169-2070(94)90052-3.

[2] Allen, P. G. (1994) „Economic forecasting in agriculture: Comment“, *International Journal of Forecasting*, Vol. 10. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0169207094900558?via%3Dihub [Accessed: 20 Aug. 2017]. ISSN 0169-2070. DOI 10.1016/0169-2070(94)90052-3.

[3] Artl, J., Artlová, M. and Rubíková, E. (2002) „Analýza ekonomických časových řad s příklady“ (in Czech), University of Economics Prague, Faculty of Informatics and Statistics, Prague, 147 p. ISBN 80-245-0307-7.

[4] Artlová, M. and Artl, J. (1995) „Grafické metody analýzy ekonomických časových řad“ (in Czech), *Statistika 32*, CZSO, Prague, Vol. 11, pp. 483-493. ISSN 0322-788x.

[5] CZSO (2016a) „*Indexy cen dodávek výrobků a služeb do zemědělství. Tabulka 1: Indexy cen vstupů do zemědělství (stejné období předchozího roku = 100“* (in Czech), CZSO, [Online]. Available: https://www.czso.cz/csu/czso/indexy-cen-dodavek-vyrobku-a-sluzeb-do-zemedelstvi-3-ctvrtleti-2016 [Accessed: 5 Aug. 2017].

[6] CZSO (2016b) „*Souhrnný zemědělský účet. Časové řady*“ (in Czech), CZSO, [Online]. Available: https://www.czso.cz/csu/czso/zem_cr [Accessed: 5 Aug. 2017].

[7] Deppermann, A., Offermann, F., Puttkammer, J. and Grethe, H. (2016) „EU biofuel policies: Income effects and lobbying decisions in the German agricultural sector“, *Renewable Energy*, Vol. 87, pp. 259-265. ISSN 09601481. 0960-1481. DOI 10.1016/j.renene.2015.10.005.

[8] E, J., Bao, Y. and Ye, J. (2017) „Crude oil price analysis and forecasting based on variational mode decomposition and independent component analysis“, *Physica A: Statistical Mechanics and its Applications*, Vol. 484, pp. 412-427. ISSN 03784371. DOI 10.1016/j.physa.2017.04.160.

[9] Enders, W. and Holt, M. T. (2012) „Sharp Breaks or Smooth Shifts? An Investigation of the Evolution of Primary Commodity Prices“, *American Journal of Agricultural Economics*, Vol. 94, No. 3, pp. 659-673. DOI 10.1093/ajae/aar162.

[10] European Commission - EU FADN (2016) „*EU Farm Economics Overview based on 2013 FADN data*“, European Commission. [Online]. Available: http://ec.europa.eu/agriculture/rica/index.cfm [Accessed: 23 Aug. 2017].

[11] European Commission (2017) „*Short-term outlook for EU agricultural markets in 2017 and 2018*“, European Commission. [Online]. Available: http://ec.europa.eu/agriculture/ markets-and-prices/index_en.htm [Accessed: 25 Aug. 2017].

[12] European Commission (2016) „*EU Agricultural Outlook, Prospects for agricultural markets and income in the EU 2016-2026*“, European Commission. [Online]. Available: https://ec.europa.eu/agriculture/markets-and-prices/medium-term-outlook_en [Accessed: 25 Aug. 2017].

[13] Galbraith, G., Bakhshi, S., Kung, W. and Kjaer, P. (2011) „Incorporating a Farm-Level Balance Sheet Forecast into the Canadian Agricultural Dynamic Microsimulation Model“, *3rd General Conference of the International Microsimulation Association*, Stockholm, Sweden.

[14] Hamjah, M. A. (2014) „Rice Production Forecasting in Bangladesh: An Application Of Box-Jenkins ARIMA Model“, *Mathematical Theory and Modeling*, Vol. 4, No. 4. [Online]. Available: http://iiste.org/Journals/index.php/MTM/issue/view/1069 [Accessed: 23 Aug. 2017]. ISSN 2225-0522.

[15] Hanke, J. E. and Wichern, D. (2008) „*Business Forecasting 9th Edition*", Pearson Education Limited, 576 p. ISBN 0132301202.

[16] Hloušková, Z., Lekešová, M., Harvilíková, M., Slížka, E. and Vrkočová, V. (2015) „Odhad ekonomických výsledků v zemědělství na základě podnikových dat FADN s nízkou či nulovou znalostí faktického vývoje odhadovaného roku"(in Czech), Final report on results of investigation of Internal research project IVP No. 1281/2014, IAEI, Prague.

[17] Hloušková, Z., Lekešová, M. and Slížka, E. (2014) „Microsimulation Model Estimating Czech Farm Income from Farm Accountancy Data Network Database", *Agris on-line Papers in Economics and informatics*, Vol. 6, No 3, pp. 27-37. ISSN 1804-1930.

[18] Hsiao, C. (2014) „*Analysis of panel data, Third edition*", Cambridge University Press. ISBN 978-1-107-03869.

[19] Hyndman, R. J. and Athanasopoulos, G. (2013) „*Forecasting: principles and practice*" OTexts: Melbourne, Australia. [Online]. Available: http://otexts.org/fpp Accessed: [Accessed: 20 Aug. 2017].

[20] Hyndman, R. J. and Kostenko, A. V. (2007) „Minimum sample size requirements for seasonal forecasting models", *Foresight: the International Journal of Applied Forecasting*, Vol. 6, pp. 12-15.

[21] Khalid, M., Sultana, M. and Zaidi, F. (2014) „Prediction of Agriculture Commodities Price Returns Using ARMA and Wavelet", *Journal of Natural Sciences Research*, Vol. 4, No. 23, 30 p. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=E2A810D4DD0F4BC4E548439370CE8C35?doi=10.1.1.663.7892&rep=rep1&type=pdf [Accessed: 20 Aug. 2017]. ISSN 2225-0921.

[22] Kostlivý, V., Fuksová, Z. and Dubec, J. (2017) „Farms Productivity Developments Based on Malmquist Production Indices", *Agris on-line Papers in Economics and Informatics*, Vol. 9, No. 2, pp. 91 - 100. ISSN 1804-1930. DOI 10.7160/aol.2017.090208.

[23] Ishaque, M., Ziblim, S. (2013) „Use of Some Exponential Smoothing Models in Forecasting Some Food Crop Prices in the Upper East Region of Ghana", *Mathematical Theory and Modeling,* Vol. 3, No. 7., pp. 16 - 27. [Online]. Available: http://www.iiste.org/Journals/index.php/MTM/article/viewFile/6373/6527. [Accessed: 26 Aug. 2017]. ISSN 2225-0522.

[24] Labys, W. C. (2003) „New Directions in the Modeling and Forecasting of Commodity Markets", *Mondes en développement*, Vol. 2, No. 122, pp. 3-19. [Online]. Available: http://www.cairn.info/revue-mondes-en-developpement-2003-2-page-3.htm. [Accessed: 23 Aug. 2017]. ISBN 9782804143022. DOI 10.3917/med.122.0003.

[25] Linden, A., Adams, J. L. and Roberts N. (2003) „Evaluating Disease Management Program Effectiveness, An Introduction to Time-Series Analysis", *Deseas Management*, Vol. 6, No. 4, pp. 243-55. ISSN 1093507X. DOI 10.1089/109350703322682559.

[26] Mošová, V. (2013) „Využití waveletů při analýze časových řad - 1. teoretická část"(in Czech), *Economics Management Innovation*, Vol. 5. [Online]. Available: http://emi.mvso.cz/EMI/2013-03/03%20Mosova/Mosova.pdf. [Accessed: 20 Jan. 2017]. ISSN 1805-353X.

[27] Natural Resources Institute Finland (2016) „*EconomyDoctor*", Natural Resources Institute Finland. [Online]. Available: www.luke.fi/en/. [Accessed: 26 Aug. 2017].

[28] OECD, FAO (2017) „*OECD-FAO Agricultural Outlook 2017-2026*", OECD. [Online]. Available: www.agri-outlook.org [Accessed: 26 Aug. 2017].

[29] Quiroga, S., Suárez, C., Fernández-Haddad, Z. and Philippidis, G. (2017) „Levelling the playing field for European Union agriculture: Does the Common Agricultural Policy impact homogeneously on farm productivity and efficiency?", *Land Use Policy*, Vol. 68, pp. 179-188. ISSN 02648377. DOI 10.1016/j.landusepol.2017.07.057.

[30] Rizov, M., Pokrivcak, J., Ciaian, P. (2013) „CAP subsidies and productivity of the EU farms", Journal of Agricultural Economics, Vol. 64, No. 3, pp. 537-557. ISSN 0021857X. DOI 10.1111/1477-9552.12030.

[31] Rural Business Research (2016) „*Farm Bussiness Survey*“, University of Cambridge, United Kingdom. [Online]. Available: http://www.farmbusinesssurvey.co.uk/index.aspx [Accessed: 20 Aug. 2017].

[32] Špička, J. (2014) „The Regional Efficiency of Mixed Crop and Livestock Type of Farming and Its Determinants“, *Agris on-line Papers in Economics and Informatics*, Vol. 6, No. 1, pp. 99-109. ISSN 1804-1930.

[33] USDA (2016) „*Farm Sector Income Forecast*“, Economic Research Service. United States Department of Agriculture. [Online]. Available: https://www.ers.usda.gov/ [Accessed: 20 Aug. 2017].