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EFFECTIVENESS AND SIGNIFICANCE OF CROP YIELD FORECAST MONITORING CONSTITUTED ON VEGETATION INDICES

Bozhidar IVANOV[1], Veselin KRUSTEV[1], Bojin BOJINOV[2]

[1]Institute of Agricultural Economics,(IAE), Agricultural Academy, 125 Tsarigradsko Shosse Blvd, Block 1, Sofia, Bulgaria, Phones/Fax: +359 884187429; +359 876 867663;E-mails: bozidar_ivanov@yahoo.co.uk; veselin.krustev@gmail.com
[2]Agricultural University, 12Mendeleev Blvd, Plovdiv, Bulgaria, Phone: +359 32 654 340; E-mail: bojinov@au-plovdiv.bg.

Corresponding author: veselin.krustev@gmail.com

Abstract

The article presents the post-hoc analysis on the crop yield forecasting on three crops across EU carried out by JRS-Mars: wheat, maize, sunflower. These crops, to less extent sunflower are one of the most widespread and grown crops across EU-27. The area occupied with those crops tallies up to 23 per cent of the utilized agricultural land and over 39 per cent of the arable land throughout EU, where in some members, including Bulgaria, their share exceeds 75 per cent of arable land. The main goal of the research is to investigate and through statistical analysis to reveal the statistical significance, effectiveness and accuracy of the crop yield forecast monitoring done by JRC-Mars, which is developed on remote sense monitoring and models set up in the of vegetation indices. The forecast results on March-April for wheat and June-July for grain maize and sunflower are juxtaposed by the actual data baseline yields. The goal of the paper is also complemented to analyze the differences in the forecast outcomes related to country's specifics, crop sensitivity and forecast time coherences. The results demonstrate that such statistical analysis are quite relevant and convincing tools to illustrate and substantiate the level of reliability of yield forecasting and that vegetation indices are appropriate element for building up yield forecasting models.

Key words: *yields, accuracy, vegetation indices, effectiveness, statistical significance*

INTRODUCTION

The grain and oilseed industries are of a great importance for the EU agriculture. Thus, the tasks for forecasting and projecting the yield and production from those staple crops in EU is considered crucial not only from the scientific point of view but also as a practical issue related to food security, coping with farmer's risk management, policymakers and commodity traders [1, 3, 16].
The EU system for information on crop growing conditions and yield forecasting was set in 1992 and is an object of a widespread interest in the academic community [20]. The yields are affected by complex and various factors - the applied production technology, farmer`s management skills and performance, climate and soil characteristics [17].
To evaluate the forecasting relevance, the following key elements are assumed – accuracy, statistical significance and effectiveness [15].
The general understanding of interpretability is to create models that are easy understandable. Such models might be linear regressions and hierarchical based models (trees) [19, 18]. A Gradient-boosted decision tree (GBDC), such as the Joint Research Center -MARS, is a standard machine learning model which demands expert interpretation to evaluate the results correctly [17].
In this paper we use basic statistical procedures based on the error – accuracy, effectiveness and significance to analyze through the statistical tool the main forecasting performance characteristics and based on it to deliberate on the robustness of vegetation indices, which are widely used as a factor for remote sense yield forecasting models.
The most interesting feature of MARS CropYield Forecasting System is to predict the "end-of-season" vegetation levels of crop production [20] when it is at completely matured quality. The most of EU-27 member states experienced their highest wheat

production harvesting in 2021, while in 2018 is estimated the lowest yield of the selected period [11]. The difference between these annual wheat yields on EU level were accounted up by12.4%while the planted area in 2021 was only 1.36% more than 2018 [5].

Average yields of maize and sunflower also had a significant volatility more than two times within the covered period. The variation in production of these two crops also had a significant scale, more than twice in difference – Romania had the poorest maize production (5.5 t/ha on 6-year average). On the other side, the highest was in Spain (11.6 t/ha), but at a cost of the lowest yield of sunflower (1.2 t/ha) in which field Croatia was the top producer with 3 tons per hectare.

The EU total (UAA) had reduced by 0.55% during the period under this study. This had a stronger impact on the crop rotation of the agricultural area. The arable land usage decreased by 2.38% [6].

The most important field crop producers are France processed arable land more than17 million hectares and Spain cultivated 11.7 in 2022 [6]. Furthermore, the rates of their land usage declines were also the most valuable – respectively 8% and 5% less than 2017. Germany (1% reduction)and Poland (2% increase) also had more than 11 million hectares. Romania had 8.2 which is 4% less than 2017 while Italy also raised the crop rotation area to more than 7 million hectares or by 2%.

MATERIALS AND METHODS

The yield forecasting in the agriculture is a complex multi-disciplinary exercise and widely explored research goal [7]. Regarding the most widespread approaches to crop yield forecasting are different statistical models, usually based on the regression and none linear modeling, and elaboration of crop-specific mechanistic models that examined in detail plant physiology and its interaction with the air and soil environments - process-based models [7]. Since 1993, the European Commission by one of its research hubs – Joint Research Center begun crop monitoring, yields and production forecasting. It has established Mars Crop Yield Forecasting System (MCYFS). The main role of the MCYFS is to provide yield statistics of the major crops at EU and national level, as accurate and timely as possible, while ensuring independence from all external sources of estimates, including the national statistical systems [8]. The JRC-MARS unit has managed to set up a comprehensive and multi-parametric system for forecasting based on meteorological analysis, agro-meteorological simulated crop growth indicators, low-resolution satellite data and statistical analysis thus it does not rely on one or limited number of factors and data sources.

The Crop Growth Monitoring System (CGMS) is under a constant upgrading and is composed of the following data factor pillars: weather indicators, crop indicators, remote sense based vegetation indices, national yield statistics, additional sources [9].

The vegetation indices are essential modules of the CGMS and those indexes are collected by remote satellite sensing. The Normalized Difference Vegetation Indices (NDVI) are most frequently applied remote sense indices, which are incorporated in the crop yield forecasting. These indices could be applied as qualitative indicators for biomass development and consequently crop yield [14].

The NDVI is thought as one of the most widely used indicator describing the level of vigour, the metabolic activity of crop, the consumption of $CO_2$by photosynthesis, of water and nutrients [2].

In the literature is revealed that the use of solely vegetation indices, regardless of what type is connected to not sufficient yield forecasting accuracy, which is due to various reasons where the leading one is that vegetation biomass factor might not be the absolute yield benchmark. It is unequivocally found that similarity in vegetation biomass crop growth recorded by vegetation indices might result in different regions and years with different harvesting yields, which reveal the inadequacy of vegetation indices as a sufficient tool for yield measuring.

The methodology of this paper is dedicated to illustrate the statistical approaches for analyzing the prognostic robustness carried out in wide range of agricultural economic studies.

The particular object of this analysis is the yield forecasting delivered by MARS bulletins on EU main crops. The purpose is not to evaluate and scrutinize the MARS methodology and forecast outcome reliability rather it is designated to demonstrate the statistical approaches in general to conduct such analyses and concretely to emphasize on the accuracy, statistical significance and effectiveness in work with vegetation indices for crop forecasting.

Velde and Nisini (2018) provide a quality assessment of MCYFS forecasts made from 1993 to 2015 focusing on accuracy, in-season, and year-to-year improvements. It is noted that accuracy of the forecasts can be investigated by calculating the mean absolute error (MAE), the mean absolute percentage error (MAPE), the root mean square error (RMSE), etc. The forecast accuracy can be analyzed in terms of forecast timing and can be defined as accuracy of early yield forecasting during the season, as well as the late forecasts a month before harvest (the pre-harvest forecast) [21].

The accuracy in this analysis is a derivation of the mean absolute error rate, which is calculated as follows:

$$MAER = \left|\frac{(FY_M - AY_M)}{AY_M}\right| \text{.................................(1)}$$

$$ACR = 1 - MAER \text{.....................................(2)}$$

where:

FY_M - yield forecast by months;

AY_M - actual yield by month;

ACR – accuracy of yield forecast.

The analysis of yield forecast based on the JRC-MARS model cover up three main and vastly grown crops in the EU – wheat, maize and sunflower. The selected forecast months are March-April for wheat and June-July for spring crops – maize and sunflower. The selected forecast months are positioned 2-3 months before harvesting of these crops, which represents about 2/3 of the vegetation period concerning wheat and more than half of the whole vegetation duration for maize and sunflower. It anticipates that the vegetation of the crops is in advanced phases and vegetation indices and meteorological data are soundly evolved and probabilistically appropriate. It is also alleged that generally the JRC-MARS system characterized with higher forecast errors at the beginning of the season and lower at the end according to a cumulative effect of the climate impact on the crop behavior [9].

The forecast error and accuracy are related statistically to plausibility and significance. The statistical significance is important criteria to accept or reject the obtained results, which in common is represented by probability (p-value). Although, the Fisherian and Neyman-Pearson schools [12] do not affirm that p-values of less than 0,05 is regarded as statistically significant whereas p-value of over 0,1indicates for not statistically significant difference [4], it is commonly accepted to infer in this direction. The determination of p-value can be done from t-statistics, using the classical formula:

$$t = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \text{..(3)}$$

In this analysis coefficient of significance is estimated by the following formula suggested by [10]:

$$CS = \frac{\bar{X} - \sigma}{\frac{\bar{X} + (N-1) * \sigma}{N}} \text{..(4)}$$

where:

$\bar{X}$ - average estimated between the yield forecast and actual yield;

σ - standard deviation between forecast and actual yield results.

The interpretation of the coefficient of significance (CS) is whenever it is higher than 1, the forecast results and actual yield results are not found different and practically they have same meaning, which complies with confirming the null hypothesis in F and Pearson statistics. This way of estimating the statistical significance of the forecasts brings simplification through obtaining certain coefficient demonstrating without needs to refer to t-statistics to conclude the likeness of results. The coefficient of significance of 1 complies with a confidence level of 67%, which is considered at critical point to accept the deviations.

The analysis of yield forecast is supplemented by an overview of effectiveness of the approach MARS model. The effectiveness is thought to show how much and to what extent the intended results are attained and how the effectiveness changes through the member states and crops. The maximum effectiveness means achieved result meets or surpass the targeted intended value. In terms of this study, maximum effectiveness is reached when the forecast and actual yield results are same and no error is calculated. The equation used for effectiveness (EFVE) is:

$$EFFE = 0.5 + \left(0.5 - \frac{MAER}{(1+MAER)}\right)............(5)$$

Thus the effectiveness can vary in the range of 0 to 1 and it takes into account the mean absolute error rate, which differently from the accuracy demonstrates the rationality and usefulness of forecast model and indirectly reveals the plausibility of vegetation indices incorporation in yield forecasting.

The observation years of the research, where the data is collected by JRC-MARS bulletins are from 2017-2022. The actual yields for selected crops are checked year later than the forecast months, i.e. the forecast yields for wheat in March-April, 2022 is validated by the MARS bulletin March-April, 2023. For the needs of result interpretation, the result ranges are assumed. The accuracy coefficients are divided into four tiers: over 0.95 – very good accuracy, 0.90 – 0.94 – good, 0.80-0.89 – moderate and less than 0.79 – generally insufficient composed of lowering grades, which are not interested for analytical purposes.

Regarding the effectiveness of the forecast tool to achieve the outcomes, the four tiers are defined as: over 0.91 – very good, 0.81-0.90 – good, 0.71-0.80 – moderate, less than 0.70 – insufficient.

RESULTS AND DISCUSSIONS

The results from analysis and statistical procession are illustrated by crops and harvesting years.

It is found that the most precise and accurate yield forecasts are achieved to soft wheat, which is characterized as the most important and widespread crop in the EU-27. The average measured forecast accuracy is estimated at 0.90 over the whole period 2017-2022.

The lowest accuracy is recorded for the crop harvest of 2018 with a moderate accuracy score at 0.84 while 2022 was with the highest accuracy outcome marked as good at 0.93.

The Netherlands and France received only good and very good statistical results which is also applicable to the common EU forecast. Most of the member states(85% of them) received good forecast accuracy, which is ranged between 0.90-0.94.

It is interesting that the JRC-MARS forecast model is working quite successfully in terms of predicting EU average yield, where the accuracy is defined as a very good level of 0.97.

By geographic cross-sectional analysis is viewed that the accuracy achieved for the North situated member states is quite more often seen compared to the same coefficient calculated for Southern member states.

Under the edge of 0.80 (but not less than 0.70) are identified a bunch of predominantly new member states: Bulgaria, Estonia, Hungary, Latvia, Lithuania.

Those states are seen with a yield forecast, which deviates in the frequent cases over the certain tolerance of forecast errors.

In that group are found the results for Romania and Estonia, where in three out of the six monitored years, the accuracy is less than 0.79 (Table 1).

Along with it, in 15% of the cases or 4 out of 26 MS is noted that in some years the yield forecasts dropped to insufficient margins.

The forecast accuracy is very unsatisfactory (0.54 – 0.59) in Spain (2017) and Finland (2018) of the explored time period. Below these levels of accuracy, worse results are measured only in other two MS – Romania (2020) and Sweden – respectively 0.41 and 0.50 (2018).

As regards the yield forecast of grain maize, the results for the accuracy are depicted as of the lowest compared to other two crops. It is estimated to 0.86, as the best predictions are achieved on forecasts for Spain and Italy up to 0.96, whereas Romania forecasts are computed up to 0.61. Altogether, three MS have good or very good accuracy results (17%) in the analyzed years – Portugal, Spain and Austria (Table 2).

Table 1. Yield forecasts accuracy of soft wheat (coeff.)

MS/ Years	2017	2018	2019	2020	2021	2022
EU	0.99	0.90	1.00	0.97	0.97	0.97
AT	0.92	*0.82*	*0.89*	*0.87*	0.97	1.00
BE	0.98	0.96	*0.89*	0.97	*0.86*	0.94
BG	0.90	*0.87*	*0.88*	**0.76**	*0.80*	0.97
CZ	0.93	*0.86*	0.96	0.96	0.97	0.97
DE	0.96	*0.80*	0.95	0.98	0.92	0.98
DK	0.91	*0.81*	0.93	0.94	0.99	0.94
EE	0.91	**0.71**	**0.73**	**0.78**	*0.88*	0.98
ES	**0.54**	*0.81*	0.94	**0.73**	*0.86*	**0.79**
FI	0.94	**0.59**	*0.85*	*0.82*	**0.77**	0.98
FR	0.99	0.92	0.92	0.91	0.99	1.00
GR	0.97	*0.80*	0.98	0.96	0.97	0.95
HR	*0.85*	0.96	0.97	0.93	*0.86*	0.99
HU	0.90	0.91	*0.87*	0.93	*0.88*	**0.71**
IE	0.96	*0.87*	0.99	*0.82*	0.93	0.93
IT	0.97	0.93	0.94	0.99	*0.84*	0.96
LT	0.96	**0.77**	*0.88*	*0.89*	*0.89*	0.95
LU	*0.88*	0.99	0.98	0.98	0.98	0.97
LV	*0.85*	**0.76**	0.92	*0.86*	0.93	0.97
NL	0.97	0.97	0.93	0.95	0.90	0.90
PL	0.94	*0.83*	0.92	0.96	0.95	0.95
PT	0.98	*0.89*	1.00	*0.86*	**0.77**	**0.79**
RO	**0.79**	1.00	0.92	**0.41**	**0.78**	*0.86*
SE	0.95	**0.50**	0.90	0.96	0.91	0.97
SL	0.97	*0.87*	0.90	0.98	*0.88*	*0.87*
SK	0.96	*0.81*	0.94	0.91	*0.89*	0.91

Source: Own calculation on the basis of data from JRC MARS 2017-2022 [11].

Germany, Greece and Poland are other three countries that have relatively high accuracy with only two years with forecasts defined by moderate meaning and in other years with good or very good qualification. Romania, Slovakia and Hungary are seen as member states, where the forecast accuracy is under the verge of reliability in most of the observed years.

The worst accuracy in yield forecasting were received by Romania (4 out of 6 were very bad), Slovenia had only one forecast where the mean absolute error rate exceeds 0.20, while Bulgaria, Hungary and Belgium have up to 2 years with relatively low accuracy over 0.80 coefficient. It should be also underlined that the maize is one of the most vulnerable in terms of yield variation crop. The yield in new member states generally is over a constant increase through the years and is positioned lower than the average yield in western member states. That is seen as one of the reason, the forecast accuracy in new MS is scored under the average outcome.

Table 2.Yield forecasts accuracy of grain maize (coeff.)

MS	2017	2018	2019	2020	2021	2022
EU	*0.89*	0.90	0.98	*0.87*	0.99	**0.72**
AT	0.96	0.98	0.96	0.91	0.93	0.90
BE	0.90	**0.65**	0.98	**0.58**	*0.85*	*0.82*
BG	0.98	*0.84*	0.95	**0.51**	*0.89*	**0.60**
CZ	0.91	**0.79**	0.90	*0.81*	*0.85*	0.93
DE	0.94	*0.80*	0.94	0.96	0.95	*0.88*
ES	0.98	0.95	0.92	0.99	0.96	0.94
FR	*0.87*	0.96	0.96	*0.88*	0.91	*0.80*
GR	0.93	0.91	0.98	*0.87*	*0.89*	0.93
HR	0.91	*0.81*	0.91	0.95	0.93	**0.64**
HU	*0.89*	*0.89*	0.95	0.91	**0.69**	**0.06**
IT	0.97	0.98	0.97	0.94	0.98	*0.89*
NL	*0.87*	**0.59**	0.95	0.92	*0.83*	1.00
PL	0.91	0.93	*0.83*	0.93	*0.84*	0.98
PT	0.90	0.95	0.95	0.95	0.93	0.97
RO	**0.67**	**0.63**	0.94	**0.37**	0.95	**0.10**
SL	*0.81*	*0.87*	*0.89*	*0.84*	0.98	**0.60**
SK	*0.89*	**0.79**	0.95	*0.89*	0.96	**0.26**

Source: Own calculation on the basis of data from JRC MARS 2017-2022 [11].

As for the sunflower forecast accuracy, it is placed at the level of 0.89, which is ranged at mid between that of wheat and maize. Within the sunflower yield forecast there is any MS that receives a top-up result. The closest to it were Italy, Slovakia and the Czech Republic. This is similar to Bulgaria, Greece where there was another one.

Croatia and Hungary have only one year with accuracy less than 0.79 but for the first country, it is estimated for 2017 while for Hungary is in 2022 harvesting year. The scope of states for the sunflower is the smallest and it set are included only 12 MS, most of them situated in eastern part of EU. The EU average yield forecast is estimated with good and very good accuracy in four of the monitored years, as in the years 2020 and 2022 the results are under the accepted reliable level of at least 0.80.

Table 3. Yield forecasts accuracy of sunflower (coeff.)

MS	2017	2018	2019	2020	2021	2022
EU	0.86	0.96	0.96	**0.77**	0.95	**0.78**
AT	*0.85*	0.94	*0.88*	*0.85*	0.90	*0.83*
BG	0.91	0.95	*0.88*	*0.80*	0.93	0.97
CZ	0.91	0.96	0.99	0.94	*0.82*	0.93
DE	0.92	*0.87*	1.00	0.95	*0.85*	*0.88*
ES	*0.83*	0.91	0.96	*0.89*	0.98	**0.72**
FR	*0.83*	0.92	0.92	**0.79**	*0.88*	0.91
GR	*0.86*	*0.84*	0.97	0.93	0.91	0.98
HR	**0.79**	0.96	0.98	0.92	0.97	0.99
HU	0.93	0.95	0.97	0.90	0.94	**0.51**
IT	0.94	0.96	0.94	0.99	0.98	*0.84*
RO	**0.68**	0.91	0.96	**0.39**	*0.89*	**0.68**
SK	0.94	0.93	0.96	0.91	0.98	*0.86*

Source: Own calculation on the basis of data from JRC MARS 2017-2022 [11].

Regarding the old member states, where generally the forecast accuracy is scored at the taller levels - Spain and France and similar to Germany and Austria, the accuracy outcomes are scored for the whole period within the range defined as very good, good or moderate without any year with insufficient coefficient. Romania had the worst results where only in two years the accuracy can be characterized as good and very good, while in other three years, the scores are deviated as insufficient.

Another part of the study is dedicated to JRC-MARS forecast effectiveness. The effectiveness testifies for the potential to reach the top-up result of accuracy and to eliminate the error. The results confirm that the forecast model works with lowest effectiveness for maize and the highest for wheat (Fig. 1).

As for the forecast period, it is revealed that as closer to the harvest is forecast so better is supposed to be the effectiveness. Through the member states, again Romania is described with the lowest effectiveness of forecasting (moderate according to the class tiers) concerning sunflower and maize (under 0.80), while concerning soft wheat, Spain has the lowest forecast effectiveness. Bulgaria, Hungary, Estonia and Finland are ranked with moderate effectiveness, while all the other MS got very good coefficients.

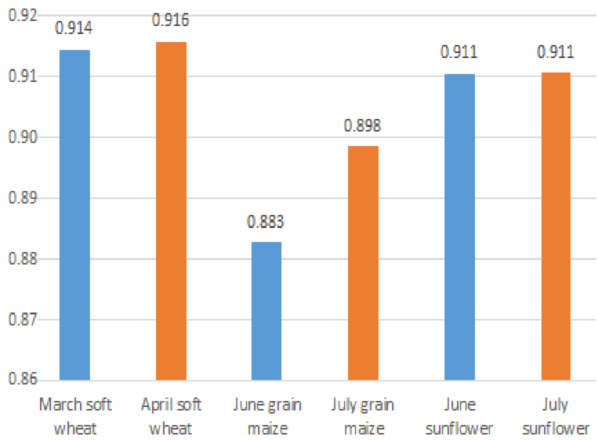

Fig. 1. Average effectiveness of yield forecasts
Source: Own calculation on the basis of data from JRC MARS 2017-2022 [11].

By statistical point of view, it is evaluated the significance of the pre-harvesting forecasts compared to actual reported yields. In almost complete set of the monitored period and member states, the results are statistically significant. It means that there is almost no difference between each one of the selected pre-harvesting months and the actual reported yield. All of the results concerning soft wheat and sunflower are in the entire observed set statistically significant. There were very few exceptions only for the maize forecasts calculated for Romania (2020 and 2022), while in 2022 forecast results are not significant to Hungary and Slovakia. The calculation of statistical significance is important study to reveal the reliability of forecast results despite of some deviations and drops in the accuracy. The statistical significance for the whole set in April-July forecast estimation is calculated at the confidence level of 94% for wheat and sunflower and 93% for maize.

CONCLUSIONS

The analysis of JRC-MARS crop forecasting covering some of the main crops for EU agriculture – wheat, maize and sunflower demonstrates the effectiveness of the forecasting model and robustness of the vegetation indices incorporated in the model. It is found out the mean absolute error rates used for estimating accuracy of yield forecasting and effectiveness are at the relatively low level between 10%-15% for March and June forecast and 10%-13% for the April-July results. Those calculations are carried out without weighting the importance and scale of the selected crop productions in different EU member states. The weighted analysis covering the first 5 biggest producers in EU (France, Germany, Poland Romania and Italy), which accounts for 64% of wheat volumes and 67% of corn quantities reaped in 2022 show the mean absolute error of yield forecasting of wheat (April) is 7,1%, whereas for maize (July) is 14,3% over the period 2017-2022 years. The weighted forecast results are scored better for the wheat compared to not weighted for all EU countries and a bit lower than the not weighted figures to all EU counties for maize. It is explained to some extent to significant level of mean absolute error for maize yield for Romania, which is ranked third biggest producer of maize in EU.

Through the ANOVA and Scheffe' tests are substantiated that principally there is not statistical difference between the forecasts carried out in March (wheat) and June (maize and sunflower) compared to a month later (April-July). The accuracy and effectiveness results of MARS forecasting are slightly better in April-July time compared to a month earlier fulfillment, which is explained by receiving and handling newer and additional data.

The yield forecasting is quite important and needed topic not only from the practical point of view but as well as from a scientific perspective. Forecasting, models, projections are not just topics and tools for analysis and research but also basis for decision-making in public and private organizations. It is assumed for the relationship between the forecast and other yield or production news appearance and the market prices or governmental policies. The robustness of forecast results is a key issue not only for the user of those results but for the implementation organizations itself. The corrections and improvements of the forecasting tools and methods is usually done after analysis of the forecast errors and accuracy. This analysis also demonstrates to a great extent that yield forecasting, which adopts in the methodology of the vegetation indices, which data is generated by remote sensing are relevant factor for such estimations improving the reliability of yield forecasting models.

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REFERENCES

[1]Basso, B., Liu, L., 2019, Seasonal crop yield forecast: Methods, applications, and accuracies. In: Advances in Agronomy. Vol. 154. Elsevier. pp. 201–255. doi: 10.1016/bs.agron.2018.11.002.

[2]Berca, M., Horoias, R., 2022, Research of the use of NDDVI in monitoring the wheat crop vegetation, the carbon storage and the yield level, on the chernozemic soils from South Romania. Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development Vol. 22(1), 35-41. https://managementjournal.usamv.ro/pdf/vol.22_1/volume_22_1_2022.pdfAccessed on March 2024.

[3]Chipanshi, A., Zhang, Y., Kouadio, L., Newlands, N., Davidson, A., Hill, H., Warren, R., Qian, B., Daneshfar, B., Bedard, F., et al., 2015, Evaluation of the Integrated Canadian Crop Yield Forecaster (ICCYF) model for in-season prediction of crop yield across the Canadian agricultural landscape, Agric. For. Meteorol., 206, pp. 137-150, 10.1016/j.agrformet.2015.03.007

[4]Dahiru T, 2008, P-value, a true test of statistical significance? A cautionary note. Ann lb Postgrad Med, 6(1); 21:26, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4111019Accessed on May 2024.

[5]Eurostat, Agricultural production – crops: https://ec.europa.eu/eurostat/statistics-explained/index.php?Accessed April 2024

[6]Eurostat, Utilised agricultural area by categories: https://ec.europa.eu/eurostat/databrowser/view/ Accessed April 2024

[7]Food and Agriculture Organization, 2016, Crop yield forecasting: Methodological and institutional aspects. Pp. 242: https://www.researchgate.net/publication/297706270_Crop_Yield_Forecasting_Methodological_and_Institutional_Aspects. Accessed on March 2024

[8]Genovese, G., 1998, The methodology, the results and the evaluation of the MARS crop yield forecasting

system. In: D. Rijks, J.M. Terres, P. Vossen (eds). Agrometeorological applications for regional crop monitoring and production assessment., Space Applications Institute, Joint Research Centre of the European Commission, Ispra, Italy, p 67-119.

[9]Genovese, G.,Bettio, M., editors, 2004, Methodology of the MARS crop yield forecasting system. Vol. 4 statistical datacollection, processing and analysis, p. 92, https://www.researchgate.net/publication/40795412_Methodology_of_the_MARS_crop_yield_forecasting_system_Vol_4_statistical_data_collection_processing_and_analysisAccessed on April 2024

[10]Ivanov, B., 2023, Factor Analysis of the Competitiveness in the Sheep Meat Production. Ikonomika i upravlenie na selskoto stopanstvo, 68(1), 20-31 (Bg).

[11]JRC MARS Bulletin, European Commission, EU Science Hub, https://agri4cast.jrc.ec.europa.eu/BulletinsArchive Accessed on March 2024.

[12]Lehmann, El., 1993, The Fisher, Neyman-Pearson theories of testing hypothesis: one theory or two? Technical Report 333. p.22: https://digitalassets.lib.berkeley.edu/sdtr/ucb/text/333.pdfAccessed on April2024

[13]López-Lozano, R., Baruth, B., 2019, An evaluation framework to build a cost-efficient crop monitoring system. Experiences from the extension of the European crop monitoring system, Agricultural Systems, Vol. 168, 231-246, https://doi.org/10.1016/j.agsy.2018.04.002: https://www.sciencedirect.com/science/article/pii/S0308521X17310259, Accessed on April2024.

[14]Meyer-Roux, J., Vossen, P., 1994, The first phase of the MARS Project, 1988-1993: overview, methods and results. In: Proceedings of conference on the MARS project: overview and perspectives, 17-18 November 1993, Belgirate, Italy, Office for Official Publications of the EU, Luxembourg, p 33-81.

[15]Molnar, C., 2022, Interpretable Machine Learning, second edition: https://christophm.github.io/interpretable-ml-book, Accessed on April2024

[16]Paudel, D., Boogaard, H., de Wit, A., van der Velde, M., Claverie, M., Nisini, L., Janssen, S., Osinga, S., Athanasiadis, I.N., 2022, Machine learning for regional crop yield forecasting in Europe, Field Crop Res, 276, Article 108377, 10.1016/j.fcr.2021.108377,

[17]Paudel, D., de Wit, A., Boogaard, H., Marcos, D., Osinga, S., Athanasiadis, I. N., 2023, Interpretability of deep learning models for crop yield forecasting, Computers and Electronics in Agriculture, Vol. 206, 107663, https://doi.org/10.1016/j.compag.2023.107663, https://www.sciencedirect.com/science/article/pii/S0168169923000510Accessed on April2024

[18]Ribeiro, M.T., Singh, S., Guestrin, C., 2016, Model-agnostic interpretability of machine learning:doi: 10.48550/ARXIV.1606.05386, https://arxiv.org/abs/1606.05386, Accessed on April2024,

[19]Rüping, S., 2006, Learning interpretable models:https://eldorado.tu-dortmund.de/bitstream/2003/23008/1/dissertation_rueping.pdfAccessed on April2024

[20]Van der Velde, M., van Diepen, C.A., Baruth, B., 2019, The European crop monitoring and yield forecasting system: Celebrating 25 years of JRC MARS Bulletins, Agricultural Systems, Volume 168, p. 56-57, ISSN 0308-521X: https://doi.org/10.1016/j.agsy.2018.10.003 https://www.sciencedirect.com/science/article/pii/S0308521X18312058Accessed on April2024

[21]Van der Velde, M., Nisini, L., 2018, Performance of the MARS-crop yield forecasting system for the European Union: Assessing accuracy, in-season, and year-to-year improvements from 1993–2015. Agr Syst. https://doi.org/10.1016/j.agsy.2018.06.009.