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# Forecasting grain yields of winter crops in Kherson oblast using satellite-based vegetation indices

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The work is devoted to the development of an early grain yield prediction model for winter cereals (wheat and barley) for Kherson oblast by the values of spatial indices (normalized differential vegetation index NDVI and enhanced vegetation index EVI), calculated on the base of satellite data. For this purpose, we conducted a regression analysis of the data to determine the correlation between the yields of the above-mentioned crops by years (for the period of 2012-2019) with the values of the vegetation indices by the months of the studied period. The region-averaged vegetation indices were calculated based on a smoothed 250-m MODIS Terrain NDVI and MODIS Terrain EVI imaginary series using GDAL QGIS 3.10 raster analysis toolkit, excluding vegetation-free zones. Based on the results of the work, models of early (30-45 days before the start of mass harvesting) high-precision winter wheat and barley grain yields according to the regional NDVI and EVI are proposed. The novelty of the research is in the development of a convenient and high-precision forecasting tool for the identification of the risks connected with food shortage and planning a strategy for the region's export capabilities and calculation of the level of local grain supply.

**Keywords: normalized difference vegetation index, enhanced vegetation index, winter wheat, winter barley, yield forecasting model.**

## INTRODUCTION

Early yield prediction is a relevant issue of modern agrarian science. Timely forecasts are useful in terms of getting information about the prospects of food security, which is directly connected to harvests, crop losses. Besides, crop forecasts help to take reasonable management decisions on crop cultivation technology, food market policy, export perspectives and needs for import of food products, etc. Crop production forecasts could be based on the results of direct observations and measurements, indirect markers of influence on crops conditions – meteorological and climate data, soil fertility indices, etc. (Bouman et al. 1997, Doltra et al. 2019, Kuchar 1989, Lykhovyd 2018). A prospective method is application of remote sensing that allows fast and precise monitoring of crops on large-scale areas through the calculation of vegetation indices, which are based on satellite imagery. Particular attention should be paid to the study of application of remote sensing to crop forecasts due to the rapid development of precision agriculture, where such models will be especially beneficial in terms of their integration into decision support systems (Jones et al. 2003, Li et al. 2015). Special attention should be paid to the development of reliable models for forecasting crops on large land arrays of regional and state level that is very important for food security and rational management of agrarian economy (Horie et al. 1992).

Kherson oblast is one of the major producer of cereals in Ukraine. Cereal crops occupied 15-30%

of total area of agricultural land in the oblast in the period of 2012-2019. Therefore, it is a relevant task of Ukrainian agrarians to work out reliable models for cereal crops forecast on the regional level.

Questions of working out reliable and easy-in-use forecasting models for crops using remote sensing data have been carefully solving for the last decades by Ukrainian and international scientific groups. There are models for large-scale crops forecast based on remote sensing meteorological data for the fields of Poland, Spain and Belgium (de Wit and Van Diepen 2008). WOFOST model for winter wheat yield in India was developed by using the remote sensing data on land cover, morphological indices of the crops with the help of regression analysis. The model has been proved to be precise and reliable for winter wheat yields forecast both on regional and state scale. It is also useful for current monitoring of the crops in India (Chaudhari et al. 2010). Chinese scientists succeeded in using remote sensing data for large-scale rice yields forecast (Wang et al. 2010). Remote sensing imagery of MODIS NDVI and MODIS EVI for the period of 2000-2010 was linked to corresponding yield data to develop the model of spring wheat yield in Western Canada. The accuracy of the model is relatively high with the fluctuation of absolute error within 2-33% (Kouadio et al. 2014). The regression model of early winter wheat yield prediction for the province Shandong in China has been developed using MODIS NDVI imagery with a resolution of 250 m. The model showed better performance than agro-climate model, relative error was just 4.62-5.40%, and the forecast is derived 40 days in advance to harvesting (Ren et al. 2008).

There is a complex regression model of winter wheat grain yield for the Steppe zone of Ukraine, developed on the basis of MODIS NDVI and MODIS NDWI imagery with a resolution 250 m. The model is based on the retrospective crop yield data for the period 2000-2013 (Semenova 2014). There are studies devoted to general interpretation and usability of spatial vegetation indices in agricultural purposes (Greben and Krasovskaya 2012, Baitsym et al. 2016). The study by Lykhovyd (2020) testifies about the possibility of using NDVI obtained at different stages of the crop development for early yield prediction of sweet corn yield. Mutual Ukrainian-American scientific group succeeded in application of remote sensing derived data in large-scale winter wheat yield prediction (Kogan et al. 2013). NDVI imagery is also used for modeling future yields of cereal crops in Ukraine by 2050 (Tarariko et al. 2016).

Considering relevance of the development of yield forecasting models on regional level it has been decided to conduct the study on derivation winter cereal crops yields in Kherson oblast through remote sensing data by the calculation of vegetation indices NDVI and EVI. Yield modeling has been performed using regression analysis because this method is one of the most common combining enough reliability and accuracy (Mkhabela et al. 2011, Yawata et al. 2019). The goal of the study is to develop models of early grain yield prediction for winter cereal crops (wheat and barley) on regional scale for Kherson oblast using remote sensing MODIS NDVI and EVI smoothed time series imagery data.

## MATERIALS AND METHODS

MODIS Terrain NDVI and EVI 16-Day 250 m smooth time series for the period 01/01/2012 – 12/31/2019 provided by the University of Natural Resources and Life Sciences (Vienna) was used to perform forecast modeling of winter crops yields. Satellite imagery was processed and cut to the boarders of Kherson oblast vegetation cover in QGIS 3.10 by the mask of vegetation provided by the NEXTGIS DATA to exclude the territories, which are free from vegetation. Means of the vegetation indices were calculated using Zonal Statistics function in the raster analysis toolkit of QGIS 3.10. Mean yields of the studied crops were taken from the reports of the Main Statistical Office of Kherson oblast. Statistical analysis was performed in BioStat v7 through the computation of Pearson's correlation coefficient R, coefficient of determination $R^2$, regression model coefficients and arguments, $R^2$ predicted, and other necessary indices and statistical criteria of regression models (Anscombe 1973, Cook and Weisberg 1982, Neter et al. 1996, Pedhazur 1997, Stevens 2002, Huber 2004, Belsley et al. 2005). The results of regression analysis were the basis for the development of yield forecasting models. The forecast were performed at $p < 0.05$.

## RESULTS

Generalized remote sensing data on the vegetation indices in Kherson oblast for the studied period are presented in the Tables 1-2.

Grain yields of winter cereal crops was performed by the values of the vegetation indices in March – May of the year of harvesting, because in the period of October – November the crops are at the initial stages of growth, which are not representative, besides, there is no guarantee for the perseverance of them in the current conditions in the winter period. The winter period is a period of dormancy, which lasts up to the end of February – beginning of March. In this time crops do not vegetate. Active regrowth of winter crops in the region usually starts in March. The computations should be performed not before this period because only after the regrowth beginning it is possible to exclude dead plants, which had not overcome winter stresses. The yields of winter wheat and barley in Kherson oblast are presented in the Table 3.

The results of preliminary determination of relationship between the yields and vegetation indices values by the months testified about the highest closure and strength of inter-connection in May. This fact is proved by the values of Pearson's correlation coefficient (Table 4-5). Therefore, the models for yield estimation should be developed for the pair of May NDVI and EVI values and winter cereal crops yields. Additionally, it was determined that the strength of connection in the pairs «grain yield of winter cereal crops – monthly MODIS Terrain NDVI» is greater than in the pairs «grain yield of winter cereal crops – monthly MODIS Terrain EVI». Higher reliability of the forecasting models based on the MODIS Terrain NDVI is also proved by the results of regression analysis (Table 6-7).

Less values of the coefficients of determination, higher values of MAPE and information criteria for the EVI-based models testify that it is advisable to use NDVI-based models in order to enhance the accuracy of the grain yield prediction. Although EVI-based model can also be applied for the purpose of winter wheat yield forecasting because the model has high enough reliability and accuracy that is approved by the coefficient of determination (0.8285 > 0.7) and MAPE (6.5170 < 10%). The forecast of winter barley grain yield is less accurate in case of EVI-based model: the coefficient of determination is 0.6366 < 0.7 and MAPE is 10.5516 > 10% (Lewis 1982, Moore et al. 2013).

By the results of regression analyses we created four forecasting models for grain yields of winter cereal crops prediction in Kherson oblast (equations 1-2 are used for the prediction of winter wheat and barley yields on the basis of MODIS Terrain NDVI obtained in May; equations 3-4 – are used for the prediction of winter wheat and barley yields on the basis of MODIS Terrain EVI obtained in May, respectively):

$$Y = -8.0022 + 21.0469 \times NDVI \quad (1)$$

$$Y = -9.0045 + 22.5430 \times NDVI \quad (2)$$

$$Y = -4.2962 + 23.7742 \times EVI \quad (3)$$

$$Y = -4.8063 + 24.7258 \times EVI \quad (4)$$

where: Y – grain yield, t/ha; NDVI – mean value of MODIS Terrain NDVI for Kherson oblast in May, points; EVI – mean value of MODIS Terrain EVI for Kherson oblast in May, points.

**Table 1: MODIS NDVI for the vegetation cover of Kherson oblast, 2012-2019**

| Year | Month | | | | | | | | | | | | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI | VII | VIII | IX | X | XI | XII | |
| 2012 | 0.34 | 0.31 | 0.33 | 0.39 | 0.46 | 0.50 | 0.51 | 0.50 | 0.49 | 0.47 | 0.46 | 0.42 | 0.43 |
| 2013 | 0.39 | 0.40 | 0.43 | 0.47 | 0.50 | 0.51 | 0.50 | 0.49 | 0.48 | 0.47 | 0.47 | 0.45 | 0.46 |
| 2014 | 0.42 | 0.42 | 0.45 | 0.49 | 0.52 | 0.52 | 0.49 | 0.46 | 0.43 | 0.42 | 0.40 | 0.36 | 0.45 |
| 2015 | 0.35 | 0.38 | 0.44 | 0.50 | 0.55 | 0.57 | 0.55 | 0.51 | 0.46 | 0.42 | 0.40 | 0.39 | 0.46 |
| 2016 | 0.39 | 0.40 | 0.45 | 0.51 | 0.56 | 0.57 | 0.56 | 0.53 | 0.49 | 0.46 | 0.42 | 0.38 | 0.48 |
| 2017 | 0.36 | 0.37 | 0.42 | 0.49 | 0.53 | 0.54 | 0.52 | 0.49 | 0.47 | 0.47 | 0.47 | 0.31 | 0.45 |
| 2018 | 0.44 | 0.43 | 0.46 | 0.50 | 0.53 | 0.53 | 0.53 | 0.51 | 0.48 | 0.45 | 0.42 | 0.39 | 0.47 |
| 2019 | 0.39 | 0.41 | 0.46 | 0.52 | 0.56 | 0.56 | 0.54 | 0.51 | 0.50 | 0.51 | 0.53 | 0.55 | 0.50 |

**Table 2: MODIS EVI for the vegetation cover of Kherson oblast, 2012-2019**

| Year | Month | | | | | | | | | | | | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI | VII | VIII | IX | X | XI | XII | |
| 2012 | 0.14 | 0.14 | 0.16 | 0.20 | 0.25 | 0.29 | 0.29 | 0.29 | 0.26 | 0.25 | 0.23 | 0.21 | 0.23 |
| 2013 | 0.19 | 0.20 | 0.22 | 0.26 | 0.29 | 0.31 | 0.30 | 0.27 | 0.25 | 0.24 | 0.22 | 0.21 | 0.25 |
| 2014 | 0.20 | 0.20 | 0.24 | 0.28 | 0.31 | 0.31 | 0.29 | 0.26 | 0.23 | 0.20 | 0.18 | 0.15 | 0.24 |
| 2015 | 0.16 | 0.18 | 0.23 | 0.29 | 0.34 | 0.35 | 0.33 | 0.29 | 0.24 | 0.20 | 0.17 | 0.15 | 0.24 |
| 2016 | 0.15 | 0.18 | 0.23 | 0.28 | 0.33 | 0.35 | 0.33 | 0.30 | 0.26 | 0.23 | 0.20 | 0.17 | 0.25 |
| 2017 | 0.16 | 0.17 | 0.21 | 0.27 | 0.31 | 0.32 | 0.31 | 0.28 | 0.25 | 0.23 | 0.21 | 0.19 | 0.24 |
| 2018 | 0.18 | 0.19 | 0.23 | 0.28 | 0.31 | 0.32 | 0.31 | 0.28 | 0.25 | 0.22 | 0.19 | 0.18 | 0.25 |
| 2019 | 0.17 | 0.19 | 0.24 | 0.30 | 0.34 | 0.35 | 0.33 | 0.30 | 0.27 | 0.25 | 0.25 | 0.24 | 0.27 |

**Table 3: Grain yields of winter wheat and barley in Kherson oblast, 2012-2019**

| Year | Winter wheat, t/ha | Winter barley, t/ha |
|---|---|---|
| 2012 | 1.69 | 1.38 |
| 2013 | 2.25 | 2.16 |
| 2014 | 2.94 | 2.44 |
| 2015 | 3.89 | 3.10 |
| 2016 | 3.62 | 3.18 |
| 2017 | 3.49 | 3.05 |
| 2018 | 3.22 | 3.47 |
| 2019 | 3.49 | 4.09 |

**Table 4: Pearson's correlation coefficient for the relationship «grain yield of winter cereal crops – monthly MODIS Terrain NDVI»**

| Crop | Month | | |
|---|---|---|---|
| | March | April | May |
| Winter wheat | 0.7455 | 0.8789 | 0.9472 |
| Winter barley | 0.8023 | 0.8935 | 0.9067 |

**Table 5: Pearson's correlation coefficient for the relationship «grain yield of winter cereal crops – monthly MODIS Terrain EVI»**

| Crop | Month | | |
|---|---|---|---|
| | March | April | May |
| Winter wheat | 0.7239 | 0.8647 | 0.9423 |
| Winter barley | 0.7457 | 0.8719 | 0.8761 |

**Table 6. Regression statistics for the relationship «grain yield of winter wheat crops – MODIS Terrain NDVI and MODIS Terrain EVI in May»**

| Criteria | Yield – NDVI | Yield – EVI |
|---|---|---|
| **Pearson's correlation coefficient (R)** | 0.9472 | 0.9426 |
| **Mean square error (MSE)** | 0.0676 | 0.0732 |
| **Coefficient of determination ($R^2$)** | 0.8972 | 0.8886 |
| **Adjusted $R^2$** | 0.8800 | 0.8700 |
| **Predicted $R^2$** | 0.8376 | 0.8285 |
| **Mean absolute percentage error (MAPE). %** | 5.7010 | 6.5170 |
| **Akaike information criterion corrected (AICc)** | 0.4392 | 0.5196 |
| **Bayesian information criterion (BIC)** | 0.3757 | 0.4561 |
| **Hannan-Quinn information criterion (HQC)** | 0.2219 | 0.3023 |
| **Intercept** | -8.0022 | -4.2962 |
| **Slope for the input (NDVI or EVI)** | 21.0469 | 23.7742 |

**Table 7. Regression statistics for the relationship «grain yield of winter barley crops – MODIS Terrain NDVI and MODIS Terrain EVI in May»**

| Criteria | Yield – NDVI | Yield – EVI |
|---|---|---|
| Pearson's correlation coefficient (R) | 0.9067 | 0.8761 |
| Mean square error (MSE) | 0.1465 | 0.1912 |
| Coefficient of determination ($R^2$) | 0.8220 | 0.7676 |
| Adjusted $R^2$ | 0.7924 | 0.7289 |
| Predicted $R^2$ | 0.7149 | 0.6366 |
| Mean absolute percentage error (MAPE). % | 8.8624 | 10.5516 |
| Akaike information criterion corrected (AICc) | 1.2125 | 1.4793 |
| Bayesian information criterion (BIC) | 1.1490 | 1.4158 |
| Hannan-Quinn information criterion (HQC) | 0.9952 | 1.2620 |
| Intercept | -9.0045 | -4.8063 |
| Slope for the input (NDVI or EVI) | 22.5430 | 24.7258 |

**Table 8: Forecast accuracy test «winter wheat grain yield – MODIS Terrain NDVI in May»**

| Pair | Grain yield, t/ha | | Residuals | | | CD | DFFIT |
|---|---|---|---|---|---|---|---|
| | true | prediction | general | standardized | studentized | | |
| 1 | 1.6900 | 1.6794 | 0.0106 | 0.0408 | 0.0715 | 0.0053 | 0.0940 |
| 2 | 2.2500 | 2.5213 | -0.2713 | -1.0434 | -1.1749 | 0.1849 | -0.6326 |
| 3 | 2.9400 | 2.9422 | -0.0022 | -0.0085 | -0.0091 | $6.18\times10^{-6}$ | -0.0032 |
| 4 | 3.8900 | 3.5736 | 0.3164 | 1.2170 | 1.3569 | 0.2239 | 0.7337 |
| 5 | 3.6200 | 3.7841 | -0.1641 | -0.6311 | -0.7375 | 0.0994 | -0.4268 |
| 6 | 3.4900 | 3.1527 | 0.3373 | 1.2975 | 1.3885 | 0.1399 | 0.5862 |
| 7 | 3.2200 | 3.1527 | 0.0673 | 0.2590 | 0.2771 | 0.0056 | 0.0970 |
| 8 | 3.4900 | 3.7841 | -0.2941 | -1.1312 | -1.3218 | 0.3192 | -0.8663 |
| Min | 1.6900 | 1.6794 | -0.2941 | -1.1312 | -1.3218 | $6.18\times10^{-6}$ | -0.8663 |
| Mean | 3.0738 | 3.0738 | – | – | -0.0187 | 0.1223 | -0.0522 |
| Max | 3.8900 | 3.7841 | 0.3373 | 1.2975 | 1.3885 | 0.3192 | 0.7337 |

**Table 9: Forecast accuracy test «winter barley grain yield – MODIS Terrain NDVI in May»**

| Pair | Grain yield, t/ha | | Residuals | | | CD | DFFIT |
|---|---|---|---|---|---|---|---|
| | true | prediction | general | standardized | studentized | | |
| 1 | 1.3800 | 1.3653 | 0.0147 | 0.0385 | 0.0674 | 0.0047 | 0.0887 |
| 2 | 2.1600 | 2.2670 | -0.1070 | -0.2796 | -0.3148 | 0.0133 | -0.1500 |
| 3 | 2.4400 | 2.7179 | -0.2779 | -0.7261 | -0.7784 | 0.0452 | -0.2895 |
| 4 | 3.1000 | 3.3941 | -0.2941 | -0.7686 | -0.8570 | 0.0893 | -0.4118 |
| 5 | 3.1800 | 3.6196 | -0.4396 | -1.1486 | -1.3422 | 0.3291 | -0.8854 |
| 6 | 3.0500 | 2.9433 | 0.1067 | 0.2788 | 0.2984 | 0.0065 | 0.1046 |
| 7 | 3.4700 | 2.9433 | 0.5267 | 1.3763 | 1.4728 | 0.1574 | 0.6411 |
| 8 | 4.0900 | 3.6196 | 0.4704 | 1.2292 | 1.4364 | 0.3769 | 0.9785 |
| Min | 1.3800 | 1.3653 | -0.4396 | -1.1486 | -1.3422 | 0.0047 | -0.8854 |
| Mean | 2.8588 | 2.8588 | – | – | -0.0022 | 0.1278 | 0.0095 |
| Max | 4.0900 | 3.6196 | 0.5267 | 1.3763 | 1.4728 | 0.3769 | 0.9785 |

**Table 10: Forecast accuracy test «winter wheat grain yield – MODIS Terrain EVI in May»**

| Pair | Grain yield, t/ha | | Residuals | | | CD | DFFIT |
|---|---|---|---|---|---|---|---|
| | true | prediction | general | standardized | studentized | | |
| 1 | 1.6900 | 1.6473 | 0.0427 | 0.1578 | 0.2908 | 0.1014 | 0.4140 |
| 2 | 2.2500 | 2.5983 | -0.3483 | -1.2868 | -1.4294 | 0.2389 | -0.7770 |
| 3 | 2.9400 | 3.0738 | -0.1338 | -0.4942 | -0.5283 | 0.0199 | -0.1867 |
| 4 | 3.8900 | 3.7870 | 0.1030 | 0.3807 | 0.4456 | 0.0367 | 0.2517 |
| 5 | 3.6200 | 3.5492 | 0.0708 | 0.2615 | 0.2904 | 0.0099 | 0.1291 |
| 6 | 3.4900 | 3.0738 | 0.4163 | 1.5380 | 1.6442 | 0.1931 | 0.7654 |
| 7 | 3.2200 | 3.0738 | 0.1463 | 0.5404 | 0.5777 | 0.0238 | 0.2051 |
| 8 | 3.4900 | 3.7870 | -0.2970 | -1.0973 | -1.2845 | 0.3054 | -0.8378 |
| Min | 1.6900 | 1.6473 | -0.3483 | -1.2868 | -1.4294 | 0.0099 | -0.8378 |
| Mean | 3.0738 | 3.0738 | – | – | 0.0008 | 0.1161 | -0.0045 |
| Max | 3.8900 | 3.7870 | 0.4163 | 1.5380 | 1.6442 | 0.3054 | 0.7654 |

**Table 11. Forecast accuracy test «winter barley grain yield – MODIS Terrain EVI in May»**

| Pair | Grain yield, t/ha | | Residuals | | | CD | DFFIT |
|---|---|---|---|---|---|---|---|
| | true | prediction | general | standardized | studentized | | |
| 1 | 1.3800 | 1.3752 | 0.0048 | 0.0110 | 0.0202 | 0.0005 | 0.0286 |
| 2 | 2.1600 | 2.3642 | -0.2042 | -0.4670 | -0.5188 | 0.0315 | -0.2343 |
| 3 | 2.4400 | 2.8588 | -0.4188 | -0.9576 | -1.0237 | 0.0749 | -0.3888 |
| 4 | 3.1000 | 3.6005 | -0.5005 | -1.1446 | -1.3398 | 0.3322 | -0.8888 |
| 5 | 3.1800 | 3.3533 | -0.1733 | -0.3962 | -0.4401 | 0.0226 | -0.1975 |
| 6 | 3.0500 | 2.8588 | 0.1913 | 0.4373 | 0.4675 | 0.0156 | 0.1643 |
| 7 | 3.4700 | 2.8588 | 0.6113 | 1.3978 | 1.4943 | 0.1595 | 0.6507 |
| 8 | 4.0900 | 3.6005 | 0.4895 | 1.1193 | 1.3102 | 0.3177 | 0.8612 |
| Min | 1.3800 | 1.3752 | -0.5005 | -1.1446 | -1.3398 | 0.0005 | -0.8888 |
| Mean | 2.8588 | 2.8588 | – | – | -0.0038 | 0.1193 | -0.0006 |
| Max | 4.0900 | 3.6005 | 0.6113 | 1.3978 | 1.4943 | 0.3322 | 0.8612 |

**Table 12: Grain yield of winter wheat and barley in Kherson oblast linked to MODIS Terrain NDVI in May**

| MODIS Terrain NDVI value in May, points | Winter wheat grain yield, t/ha | Winter barley grain yield, t/ha |
|---|---|---|
| 0.2-0.3 | No yield | No yield |
| 0.3-0.4 | ≤0.40 | ≤0.05 |
| 0.4-0.5 | 0.40-2.50 | 0.05-2.25 |
| 0.5-0.6 | 2.50-4.65 | 2.25-4.50 |
| 0.6-0.7 | 4.65-6.75 | 4.50-6.75 |
| 0.7-0.8 | 6.75-8.85 | 6.75-9.00 |
| >0.8 | >8.85 | >9.00 |

**Table 13: Grain yield of winter wheat and barley in Kherson oblast linked to MODIS Terrain EVI in May**

| MODIS Terrain EVI value in May, points | Winter wheat grain yield, t/ha | Winter barley grain yield, t/ha |
|---|---|---|
| 0.2-0.3 | 0.40-2.80 | 0.15-2.60 |
| 0.3-0.4 | 2.80-5.20 | 2.60-5.10 |
| 0.4-0.5 | 5.20-7.60 | 5.10-7.55 |
| 0.5-0.6 | 7.60-9.95 | 7.55-10.00 |
| >0.6 | >10.00 | >10.00 |

The results of approximation and forecast tests are presented in the Table 8-11. CD is an abbreviation of Cook's distance, and DFFIT – difference in fitting (Belsley et al. 1980, Cook and Weisberg 1982).

The results of approximation fitting and forecast accuracy test demonstrate higher efficiency of MODIS Terrain NDVI implementation for winter cereal crops grain yields prediction in Kherson oblast.

Based on the developed models, scales of the crops grain yields were created to simplify the application of the study results in practice (Table 12-13). Values of NDVI, which are below 0.2, are considered to represent extremely poor or no lively vegetation present (Birsrat and Berhanu 2018). EVI values of less than 0.2 are also considered to represent unhealthy, weak vegetation or nearly bare landcover (Fraga et al. 2014).

## DISCUSSION

The developed regression models of winter cereal crops yield prediction in Kherson oblast allow early (30-45 days in advance) estimation of possible grain yields in the region. The models can be used as they are now. Their accuracy is relatively high (predicted $R^2$ fluctuates within 0.6366-0.8376). However, we find it necessary to improve the quality of yield prediction to work out the models with MAPE < 5% and predicted $R^2 \geq 0.95$ at $p < 0.05$. There are several ways of the enhancement in the model performance. First, we are going to add new yield and remote sensing derived data each year to increase the number of inputs and outputs. Another way is a try of other computation techniques, for example, artificial neural networks, which frequently perform better in yield forecasting than common regression (Lykhovyd 2018). Besides, introduction of combined models, for example, MODIS NDVI plus meteorological indices (Saeed et al. 2017), MODIS NDVI plus LAI (Patil et al. 2012), often results in improved reliability and accuracy of yield predictions. In our case, it is possible to implement all the above methods and techniques for the models' enhancement. Even better results could be obtained through additional computations involving the most recent satellite derived vegetation indices, for example, general yield unified reference index or GYURI (Ferencz et al. 2004).

Besides the enhancement of the models' accuracy, another useful thing is building yield maps based on remote sensing data (Fortes Gallero et al. 2015). Solving this task requires imposition of the field maps on the NDVI or EVI distribution maps with further association of different parts of the fields with corresponding model yield values.

## CONCLUSION

Regression models of early (30-45 days before harvesting) grain yield prediction of winter wheat and barley have been developed for Kherson oblast on the basis of remote sensing derived MODIS Terrain NDVI and EVI values in May. Statistical evaluation and test of the developed models testifies about their high reliability and accuracy. The best performance is demonstrated by NDVI-based models..

## CONFLICT OF INTEREST

The authors declared that present study was performed in absence of any conflict of interest.

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## AUTHOR CONTRIBUTIONS

PL designed and performed the study and also wrote the manuscript. SL and NL provided some additional statistical data and reviewed the manuscript. All authors read and approved the final version.



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